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THESIS

AN ANALYSIS OF THE JOINT STRIKE FIGHTER AUTONOMIC LOGISTICS SYSTEM

by

Anastasios Tsoutis

September 2006

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Traditionally in the Navy/Marine Corps, in an effort to be proactive and prevent failures, maintenance and inspections are performed at fixed intervals independent of aircraft status. The current preventive maintenance strategy services and replaces certain components on a pre-determined schedule. Additionally, the current Navy/Marine Corps aircraft repair process is reactive. First failures occur, then the logistics system – maintenance and supply – respond. The Joint Strike Fighter Autonomic Logistics System (ALS) is proposed to be better then the logistic system in place. Under the ALS maintenance is performed only as needed. The idea is to decrease the logistics infrastructure and simultaneously improve logistic performance, by performing maintenance only as needed. Additionally, parts are ordered 'autonomously' without human intervention. The logistics system prepares for an impending failure. In the thesis simulations are developed to compare the traditional repair system and the ALS. An analysis is conducted to show differences in performance in respect to aircraft availability, failures per mission and maintenance-man-hour-per-flight-hour. The ALS maintenance model dominated traditional maintenance under the study assumption.

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AN ANALYSIS OF THE JOINT STRIKE FIGHTER AUTONOMIC LOGISTICS SYSTEM

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ABSTRACT

Traditionally in the Navy/Marine Corps, in an effort to be proactive and prevent failures, maintenance and inspections are performed at fixed intervals independent of aircraft status. The current preventive maintenance strategy services and replaces certain components on a predetermined schedule. Additionally, the current Navy/Marine Corps aircraft repair process is reactive. When failures occur, the logistics system – maintenance and supply – respond. The Joint Strike Fighter Autonomic Logistics System (ALS) is proposed to be better then the logistic system in place. Under the ALS maintenance is performed only as needed. The idea is to decrease the logistics infrastructure and simultaneously improve logistic performance, by performing maintenance only as needed. Additionally, parts are ordered 'autonomously' without human intervention. The logistics system prepares for an impending failure. In this thesis simulations are developed to compare the traditional repair system and the ALS. An analysis is conducted to show differences in performance in respect to aircraft availability, failures per mission and maintenance-man-hour-per-flight-hour. The ALS maintenance model dominated traditional maintenance under the study assumptions.

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THESIS DISCLAIMER

The reader is cautioned that the computer program developed in this research may not have been exercised for all cases of interest. While every effort has been made, within the time available, to ensure that the programs and data herein are free of computational, logic, and collection errors, they cannot be considered validated. Any application of these programs or data without additional verification is at the risk of the user.

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LIST OF ABBREVIATIONS AND ACRONYMS

AIMD	Aircraft Intermediate Department
ALS	Autonomic Logistic System
CLT	Central Limit Theorem
DES	Discrete Event Simulation
D-Level	Depot Level of Repair
DoD	Department of Defense
FPH	Failures per Flight Hour
FPM	Failure per Mission
I-Level	Intermediate Level of Repair
JDIS	Joint Distributed Information System
JSF	Joint Strike Fighter
LRU	Line Replacement Unit
MMHF	Maintenance Man Hours per Flight Hour
MOE	Measure of Effectiveness
NAMP	Naval Aviation Maintenance Program
O-Level	Organizational Level of Repair
PHM	Prognostics Health Management

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EXECUTIVE SUMMARY

Traditionally in the Navy/Marine Corps, to proactively prevent failures, maintenance and inspections are performed at fixed intervals independent of aircraft status. The current preventive maintenance strategy services and replaces certain components on a predetermined schedule. Additionally, the current Navy/Marine Corps aircraft repair process is reactive. First failures occur, then the logistics system – maintenance and supply – respond.

The Joint Strike Fighter Autonomic Logistics System (ALS) is proposed be better then the logistic system in place. Under the ALS, maintenance is performed only as needed. The idea is to decrease the logistics infrastructure and simultaneously improve logistic performance by performing maintenance only as needed. Additionally, parts are ordered "autonomously" without human intervention. The logistics system prepares for an impending failure.

Simulations described in this thesis compare the traditional repair system and the ALS. An analysis shows the differences in performance in respect to aircraft availability, failures per mission and maintenance-man-hour-per-flight-hour.

Due to an absence of JSF history and data on JSF maintenance processes, the analysis is performed using an existing aircraft. The simulations are based on the Navy's F/A-18E/F jet engine repair process. The aircraft will not be replaced by the JSF, so it may be beneficial to alter the aircraft in order to take advantage of the ALS.

This thesis introduces two simulations. One simulation is for the traditional, F414-GE-400 aircraft engine repair process, currently in place. The other simulation is for the F414-GE-400 aircraft engine repair process under the ALS. Stochastic models developed are used in a face validation of the DES models. Design points for the simulations are selected using a Nearly Orthogonal-Latin Hypercube (NOLH) design. Regression models are produced to define the relationship between each of the MOEs and the predictor variables. The FPM regression models are used to compare the traditional repair system and the ALS.

The ALS maintenance model dominates in terms of flights per mission (FPM) and maintenance man hour per mission (MMHF). However, large gains in operational availability were not realized. In terms of FPM, when deciding between investing in module reliability in the traditional repair system or prognostic accuracy it is best to invest in prognostics and switch to the ALS. In terms of MMHF, the ALS potential far exceeds that of the traditional system. The ALS is superior to the traditional system.

I. INTRODUCTION

A. BACKGROUND/AREA OF RESEARCH

1. Introduction

In November 2002, Department of Defense (DoD) policy directed the military services to implement the tenets of Conditioned Based Maintenance Plus (CBM+) in weapons systems and logistics support programs where cost effective. CBM+ focuses on predicting maintenance needs and responding accordingly. The idea is to decrease the logistics infrastructure and simultaneously improve logistic performance by performing maintenance only as needed. “The Joint Strike Fighter (JSF) Prognostics Health Management System (PHM) is highlighted as an “emerging” example of a true prognostics-capable aircraft embodying the full intent of the CBM+” (Smith, 2003).

Prognostic capability alone does not improve the entire maintenance and logistics system. “Prognostic capability may properly identify a material requirement, but the requirement must be transmitted, received, filled, transported, and delivered to provide a solution to the maintainer” (DoD, 2004). A logistic network where real time maintenance and supply needs are known is essential for faster support. This is in agreement with the “sense and respond logistics” concept. The customer has only what they need when they need it. For this to be viable, “logisticians need to be able to communicate with customers, to know where they are geographically, to know what they are doing…”(Schrady, 2005).

To take advantage of its prognostic capability, and to accelerate the logistics process, the JSF PHM comes as part of an Autonomic Logistics System (ALS) that includes a distributed information system. According to the JSF website: The JSF will achieve unprecedented levels of reliability and maintainability, will be the most supportable aircraft, and will be ready to fight anytime and anyplace (F-35, 2006).

2. Preventive Maintenance/Reactive Support

Traditionally in the Navy/Marine Corps, to proactively prevent failures, maintenance and inspections are performed at fixed intervals independent of aircraft status. The current preventive maintenance strategy services and replaces certain

components on a pre-determined schedule. This periodic maintenance depends strictly on flight hours accumulated on the component (age). Preventive maintenance is independent of the component's condition. Scheduled/preventive maintenance wastes time and money; some of the scheduled maintenance is unnecessary. Only 23% of aircraft equipment failure patterns are age related, 77% are random (Sondalini, 2003). For random failures, one cannot predict when a failure occurs based only on age.

Additionally, current logistics and maintenance support are reactive. First failures occur, then the logistics system – maintenance and supply – respond. The maintenance personnel troubleshoot to isolate the problem, then order the part and wait for supply to requisition the request. Time is wasted while waiting on parts. The Automated Logistics system (ALS) remedies these two areas: scheduled maintenance based on age and responsiveness to failure.

3. Autonomic Logistics System

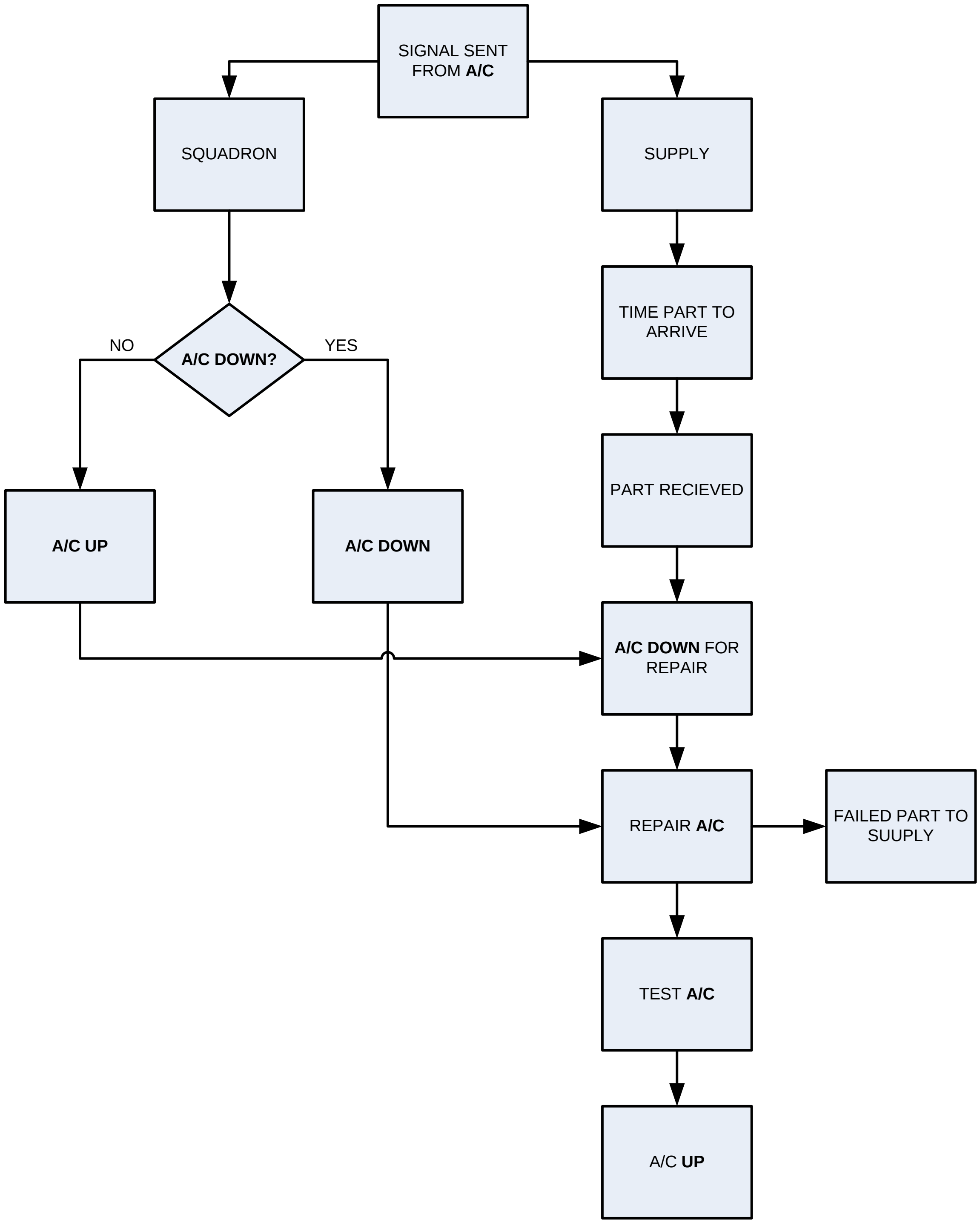
An Autonomic Logistics System (ALS) is a system that automatically responds to maintenance/failure events. Tasks such as identifying failures and ordering parts are executed without human intervention. "The JSF Autonomic logistics system encompasses three essential components: (1) a highly reliable, maintainable, and intelligent aircraft that incorporates Prognostics Health Management (PHM) technology; (2) a technologically-enabled maintainer, capable of effectively and efficiently maintaining the JSF; and (3) a Joint Distributed Information System (JDIS) that incorporates advanced information system technology to provide decision support tools and an effective communication network linking the JSF with the logistics infrastructure" (Hess, 2004)**.**

The key to the JSF Autonomic Logistics is the ability to detect and predict failures. These capabilities in conjunction with the other essential components not only have the potential of saving time but make a policy of condition-based maintenance a realistic one. This way maintenance is performed only as needed. Another benefit to predicting failures is to stop disabling failures and fatal failures before they occur.

The PHM technology incorporates:

- Diagnostics – the process of determining the state of a component to perform its function(s)
- Prognostics – predictive diagnostics which includes determining the remaining life or time span of proper operation of a component
- Health Management – the capability to make appropriate decisions about maintenance actions based on diagnostics/prognostics information, available resources and operational demand" (Hess, 2006).

Ideally the PHM detects/predicts a component failure and instantaneously relays this immediately to the appropriate entities. The ALS automatically provides details of the cause and location of the failure; troubleshooting is eliminated. Additionally, required parts are ordered automatically eliminating the requirement to manually order parts and reducing the time for a part to arrive. The ALS will provide the required number of personnel to repair the failure and will locate available parts. Knowing a failure will occur in advance allows additional time for preparation and flexibility in scheduling maintenance. For example, if a failure was detected 30 hours in advance, the squadron may decide to continue using the aircraft until the parts arrived. See Figure 1 for overview of process.



A/C - aircraft
UP - A/C is mission capable, can fly, can be scheduled for a mission
DOWN - A/C non-mission capable, cannot fly, cannot be scheduled for a mission

Figure 1. JSF Autonomic Logistic Flow Chart

4. Assumed Benefits of the ALS

By predicting failures and accelerating information flow the ALS has potential to decrease the downtime of the aircraft and to reduce cost. A financial advantage may exist despite the fact there is an expense in setting up and maintaining the ALS. An Army/Marine CBM+ initiated program to develop prognostics on helicopters has proven to increase readiness. However, few helicopters are installed with the equipment, as costs exceed $1 million dollars per aircraft (Messenger, 2004).

The expectations for the ALS are high. It is anticipated there will be a forty to fifty percent savings in manpower and infrastructure cost at unit level while simultaneously turn around time will be in minutes instead of hours (Adams, 2003). Supposedly, aircraft readiness will increase, down time for repairs will decrease, required number of maintenance personnel will decrease, and reducing cost.

Dr. Scheuren heads the Defense Advanced Research Projects Agency's (DAPRA) Joint Advanced Strike Technologies (JAST) Program. In his view, "both the ultimate objective of PHM and its related autonomic logistics system is to reduce maintenance manpower requirements by approximately 20% to 40%, increase combat sorties by 25%, and reduce the complexity of the logistics trail by 50%, compared to current military strike aircraft; all at a cheaper life cycle cost as compared with legacy aircraft" (Nickerson, 1998).

Rebulanan constructed a simulation of the basic framework of an ALS (ALSim) as a tool to allow comparison between ALS and the current maintenance process (Rebulanan, 2000). His model showed that higher aircraft availability could be obtained with an ALS. Rebulanan assumed the prognostics were 100% accurate and maintainers were always available. One would expect ALS with 100% accurate prognostics to perform better than the current system. What if the prognostics were not 100%? In this case, false detections and/or missed detections are possible. With a false detection, the logistics system is unnecessarily burdened. Advantages and disadvantages for the current and ALS processes are summarized below.

Current System:

Advantages

- Scheduled/Preventive maintenance may prevent catastrophic failure, thus exposing the underlying cause of such a failure. Under ALS these causes may be masked.

Disadvantages

- Fault occurs, then maintenance must wait for aircraft to land to determine problem.
- High time to troubleshoot aircraft (includes diagnostics, it takes time to retrieve information)
- Time taken to order part and wait for delivery (aircraft may be unusable).
- Wasted resources: scheduled maintenance replaces parts that may not need replacing. Other maintenance performed that may not be required.
- Wasted time: unnecessary scheduled maintenance takes time.

ALS system:

Advantages

- Fault detected before it occurs, and information is relayed instantaneously.
- Parts are automatically ordered, saving time.
- No troubleshooting; therefore saves time.
- Can plan maintenance for aircraft at ideal time, i.e. when part is delivered.
- No scheduled/preventive maintenance saving man-hours, cost and increasing readiness.

Disadvantages

- False alarms may cause unnecessary part replacement and maintenance.
- Chance of not detecting a failure.
- The time from detection of a degraded component until failure may be too short or too variable to gain benefits.
- Cost of sensors, communication equipment, etc.

B. RESEARCH OBJECTIVES / PURPOSE

The JSF ALS promises to perform better than compared to the current system. The intent of the thesis is to examine how the ALS performs. The ALS automatically orders parts based on the PHM. For a PHM with various degrees of accuracy, failure

detection times and false alarm rates - including JSF ORD (operational requirement document) requirements - determine the logistic implications, e.g. parts ordered in error that were not needed. Indicators of how well the logistic system is doing include: time for maintenance to receive a part, time aircraft is down and number of components replaced needlessly. Additionally, this thesis estimates the maintenance time saved compared to using current policies and the difference in aircraft readiness.

Critical factors for the traditional repair system and the ALS are identified. The factors are used to compare both systems. The purpose of this thesis is to provide analytic support for the hypothetical benefits of the ALS over the current system. The model will aid in determining how the ALS will perform, and therefore, help decision makers determine how much to invest.

C. SCOPE AND ASSUMPTIONS

The current logistics structure with the ALS is shown in Figure 2. The JDIS component is assumed to work perfectly, and so will not be considered. If the PHM on board predicts a failure, a signal is generated. Signals from the aircraft are assumed instantaneously received, without interference. Information is available real time. The signal initiates what parts are ordered and the maintenance actions needed.

The ALS still requires human involvement to accomplish tasks. As an example parts are ordered autonomously but a supply clerk is needed to fill the requisition. Therefore, there may be delay for a human to respond to the message. The autonomic driven actions respond immediately to the signal. Human response to the signal depends on availability and capability of personnel. However, in this study, it is assumed that capable personnel are always available.

Prognostics *are not* presumed to be 100% correct/accurate. As a result one of the following scenarios may occur:

(1) PHM accurately predicted the failure.

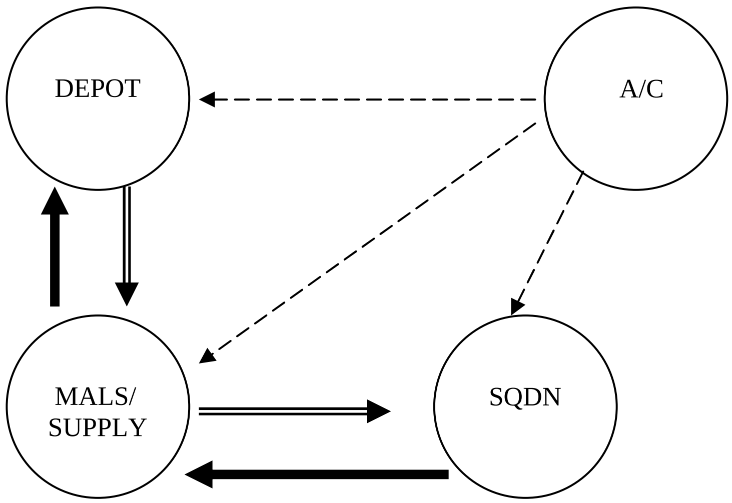
(2) False alarm: PHM sends signal when no failure is to occur.

(3) PHM does not predict/send signal before the failure actually occurs.

Additional Assumptions:

(1) Diagnostics *are* 100 % accurate. Once a failure is predicted, the fault is accurately isolated.

(2) The manufacturer/depot has unlimited resources and replaces all non-ready for issue (NRFI) line replaceable units (LRU) immediately.



Signal sent from aircraft (A/C)

Path of RFI (ready for issue) part

Path of NRFI (Not ready for issue) part

Squadron (SQUAD) where maintenance performed

Figure 2. JSF Autonomic Logistic Structure

D. PRIOR WORK

In 2000, Capt. Rene Rebulanan, United States Air force, wrote a thesis to examine how the ALS performs and what demands it places on the logistics infrastructure (Rebulanan 2000). Using the Java programming language he developed an ALS simulation model. For a set of four aircraft he showed the difference in flying the aircraft with ALS and without ALS (the traditional system). Aircraft characteristics were based on the F-16. The simulation was run for to simulate six months. Rebulanan concluded that the ALS leads to higher availability. Rebulanan assumed the prognostics worked all

the time, that is impending failures were always detected. This thesis explores the impact of prognostics that are not 100% accurate. Additionally, this thesis implements a squadron worth of aircraft, and analyses the impact on the O and I levels over the lifetime of the aircraft (assumed to be 25 years).

In 2003, Lieutenant Commander, Eric J. Schoch, wrote a thesis that models the F414-GE-400 engine repair process. The goal of the simulation was to provide operational availability and probability to spare the process given the current system in place, which does not incorporate the ALS. His simulation utilizes the Java package Simkit, a software package for implementing Discrete Event Simulation (DES) models (Buss, 2001). Schoch's model accounts for all the squadrons and AIMDs in the United States Navy. This thesis will implement only one AIMD and the squadrons it supports. Schoch's model mimics the depot with same level of detail as the AIMD, and depot inventory levels and turn around times are considered. The logistic impact on the depot falls outside the scope of the thesis. The depot is assumed to have a replacement on hand. This thesis develops a simulation for the F414-GE-400 repair process augmented with ALS.

E. METHODOLOGY

Because of the absence of history and data on the JSF maintenance processes, the analysis will be performed using an existing aircraft. The model is based on the Navy's F/A-18E/F jet engine repair process. Therefore, model runs are based on the Naval Aviation Maintenance Program (NAMP). Two F-414-GE-400 engines power the F/A-18E/F. The line replacement units (LRU) simulated are the F-414-GE-400 engine and its subcomponents.

A Discrete Event Simulation (DES) model represents the current F-414-GE-400 engine repair process. With a DES model one can observe the behavior of the system over time. The DES program is based on Lieutenant Commander Schoch's simulation work so it is also implemented in Simkit (Schoch, 2003). Multiple runs (with multiple replications) for the current system model are used. The effect of changing the input parameters on the measures of effectiveness (MOE) is explored.

The model will then be augmented with the essential elements of the ALS: PHM and JDIS. The ALS model is run multiple times using various prognostic accuracies, detection times and false alarm rates. Example ranged include prognostic accuracies: 90, 95 and 100%, detection times: 10, 20 and 30 hours before failure time and mean flight hours between false alarms 450 and 700. The same LRU failure patterns for both the legacy system and the ALS are used. For each level of accuracy, expected different values of the MOE are observed. For some level of accuracy and below the ALS may offer little or no improvement.

Simulation results for each system are compared to determine the benefits of the ALS. Three MOEs are considered. The primary MOE is operational availability: time the aircraft are available for a mission divided by the total time of the simulation run. The other MOEs considered are *maintenance man hours per flight hour* (MMHF) and *number of failures per flight mission* (FPM).

Additionally, a stochastic model is developed for each system. The purpose of the stochastic model is to analyze key elements of the logistics system. The results from the stochastic model are a face-validation of the DES model.

The thesis consists of five steps:

1. Create a Discrete Event Simulation (DES) using Simkit for the current F414-GE-400 engine repair process.
2. Augment the current F414-GE-400 engine repair process model with ALS.
3. Develop stochastic models and use them to verify the DES model.
4. Exercise the DES model using F/A-18E/F data.
5. Analyze results of simulation and draw conclusions.

The analysis shows that ALS maintenance model dominates in terms of flights per mission (FPM) and maintenance man hour per mission (MMHF). However, large gains in operational availability were not realized. In terms of FPM, when deciding between investing in module reliability in the traditional repair system or prognostic accuracy it is best to invest in prognostics and switch to the ALS. In terms of MMHF, the ALS potential far exceeds that of the traditional system. Thus, the analysis supports the conclusion that ALS is superior to the traditional system.

F. ORGANIZATION

Chapter II, Logistics Process, describes the current F414-GE-400 aircraft engine repair and the F414-GE-400 engine repair with ALS processes. Additionally Chapter II covers data used to model the engine repair process. Chapter III describes the DES model. Chapter IV contains the stochastic models. In this chapter, results from simulations using the DES and stochastic models are compared. Chapter V discusses the experimental design. Chapter VI is the analysis of the MOEs. Finally, Chapter VII provides conclusions and further recommendations.

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II. F414-GE-400 AIRCRAFT ENGINE REPAIR PROCESS

Due to the absence of history and data on the JSF engine maintenance processes, the F/A-18E/F 'Super Hornet' engine, F-414-GE-400, is used for this study. The F/A -18E/F is the latest tactical aircraft to enter the United States Navy. It will not be replaced by the JSF so it may be beneficial to alter the aircraft in order to take advantage of the ALS. The purpose of this chapter is to describe the F414-GE-400 Aircraft Engine Repair Process and give an overview of the data and assumptions.

A. F-414-GE-400 ENGINE

Two engines power the F/A-18E/F. The F-414-GE-400 consists primarily of six modules: The fan, compressor, combustor, high pressure turbine, low pressure turbine and afterburner. The engine is designed for easier more efficient maintenance and the modules are fully interchangeable.

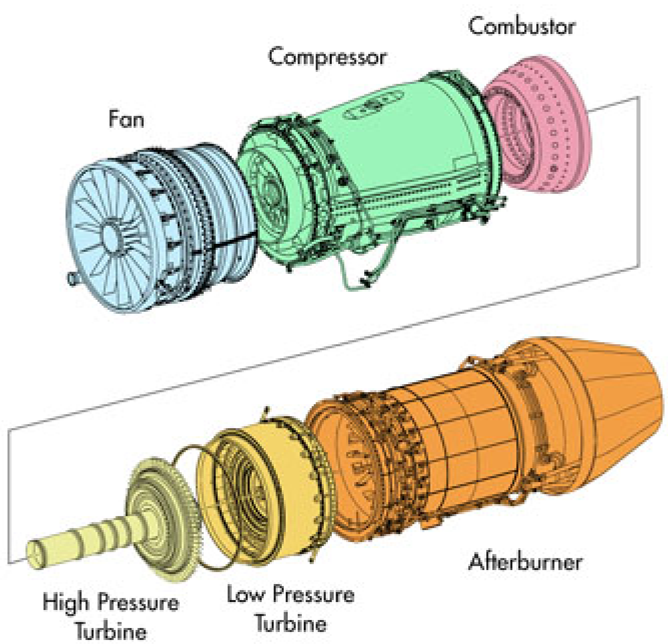

Figure 3. F414-GE-400 (General Electric, 2003)

B. THREE LEVELS OF MAINTENANCE

The Naval Aviation Maintenance Program (NAMP) is founded upon the three-level maintenance concept: Organizational (O), Intermediate (I) and Depot (D). As the operating unit, the squadron performs the lowest level of maintenance: organizational

maintenance. The Aviation Intermediate Maintenance Depot (AIMD), located at air stations, as well as deployed aircraft carriers, performs the intermediate level maintenance. The naval aviation industrial establishment performs the depot level maintenance. For the FA-18E/F, the engine repair process is identical while afloat or onshore.

The squadron performs maintenance to support its daily operations. The squadron performs limited repair, which includes engine trouble shooting, and removal and installation. The engine is removed when a failure that cannot be repaired occurs or when one its modules is scheduled for replacement.

Traditionally, AIMD has extensive maintenance capabilities. However, I-level support for the F14-GE-400 is limited. Limited I-level support is also planned for the JSF. The AIMD has the ability exchange modules on an engine and assemble engines. The AIMD does not repair modules. Modules in need of repair or preventive maintenance are sent to a naval aviation industrial establishment.

For the F414-GE-400, there is only one naval aviation industrial establishment, the Naval Aviation Depot at Jacksonville, Florida. “The D-level is the top echelon of the jet aircraft engine repair process and can perform all maintenance and repair action” (Schoch, 2003).

C. F/A18-E/F ENGINE REPAIR CYCLE

When an engine failure is detected, the squadron troubleshoots to isolate the cause of failure. The engine is removed if the failure cannot be repaired at the O-level. Additionally, engines are removed if any of the modules has reached ‘high time.’ High time is a predetermined time when the module is scheduled for removal. High times prescribe the removal of modules based on hours of operation. When a module reaches high time, it is removed regardless of its current condition. Module high times are listed in Appendix A. Figure 4 illustrates the O-level echelon maintenance.

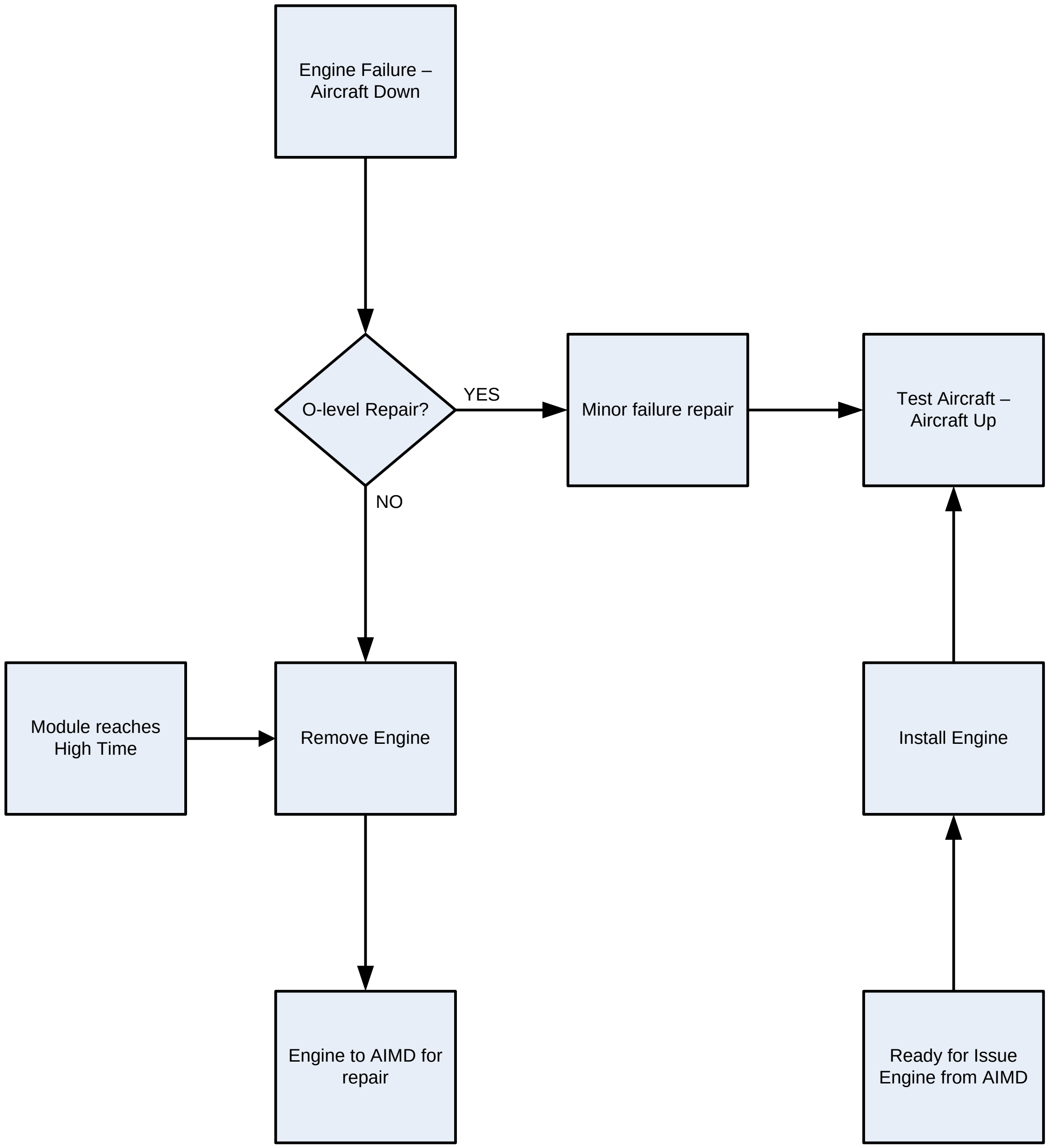

Figure 4. O-level F414-GE-400 Engine Repair

Managing an engine pool and a module pool is a key function of the AIMD. The AIMD has the ability to disassemble and assemble engines. Modules that need repair, to include preventive maintenance, are sent to the depot. A squadron that needs an engine receives a ready for issue (RFI) engine from the pool. As long as there is an engine in the inventory, the squadron does not have to wait for the removed engine to be repaired.

AIMD inspects all engines received from the squadrons. Modules in need of repair or preventive maintenance are replaced. AIMD has the option of replacing modules with modules in the pool or usable modules from other engines waiting assembly. As engines are assembled, they are added to the pool.

At the I-level, a module is considered in need of preventive maintenance if it has reached high time or if it is within a certain range of high time. This range of time is called ‘build window.’ For example, if an engine with a build window of twenty hours is sent to the AIMD, modules within twenty hours of high time are replaced. Figure 5 illustrates the I-level echelon maintenance.

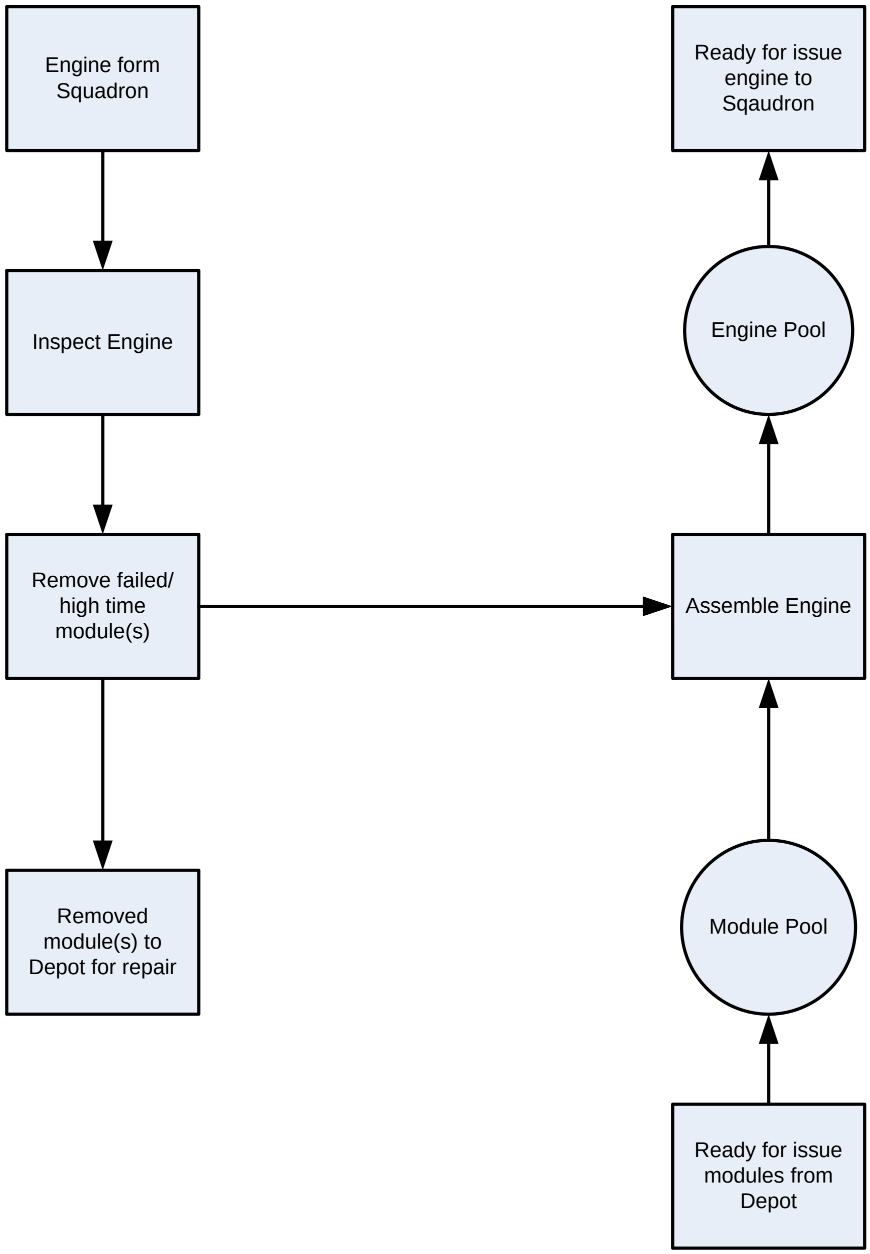

Figure 5. I-level F414-GE-400 Engine Repair

The Naval Aviation Depot at Jacksonville, Florida repairs modules. It is the responsibility of the Depot to replace modules turned in from the AIMD. Like the AIMD, the depot has an inventory pool in which to issue modules.

D. ALS F/A18-E/F ENGINE REPAIR CYCLE

Under the ALS, aircraft are enabled with the PHM system. The system monitors the current condition of the engine and forecasts impending failures. In flight, when the

PHM detects any degradation of the engine, it will isolate the failure and predict the remaining life of the engine. Note that the PHM is not 100% accurate. False detections and/or missed detections may occur. A signal containing this information is sent from the aircraft to each of the three levels of maintenance thereby autonomously initiating action at each level.

The squadron does not troubleshoot engines nor does it remove modules on the high time schedule. Upon receiving an impending failure message the squadron will decide when to remove the engine from the aircraft. Ideally, the engine removal can occur to coincide with the arrival of the replacement engine. Aircraft will no longer sit inoperable while waiting for a replacement. The longer the lead time (predicted remaining life of engine) the more flexibility the squadron has. The squadron has two options: to abort the mission then ground the aircraft, or not ground the aircraft and schedule the aircraft for follow on missions. Figure 6 illustrates the O-level echelon maintenance at the squadron.

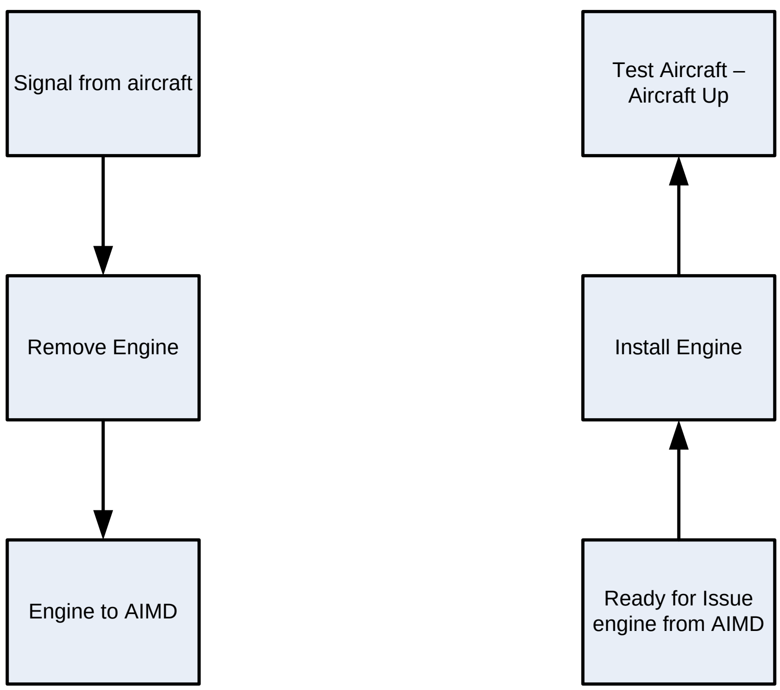

Figure 6. ALS O-level F414-GE-400 Engine Repair

When an impending failure message from the aircraft, is received at the I-level, an engine is sent to the squadron. The degraded engine is brought back to the AIMD. The

AIMD no longer performs inspections. The PHM directs replacement of the module that caused the failure. The degraded module is then sent to the depot. The depot automatically sends a RFI module to the AIMD and waits for the degraded module. Figure 7 illustrates the I-level echelon maintenance.

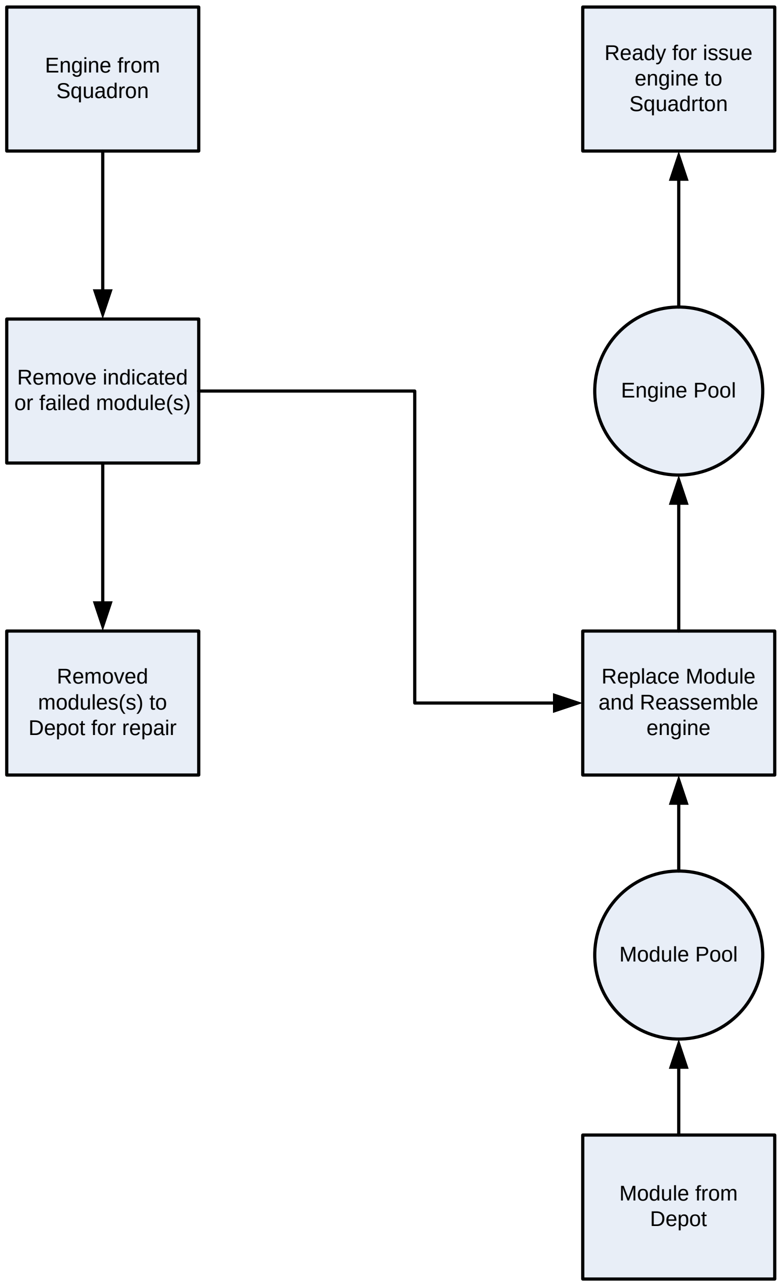

Figure 7. ALS I-level F414-GE-400 Engine Repair

E. ASSUMPTIONS

1. Assumptions Applicable from Schoch's Thesis

The simulation uses the following assumptions from Schoch's thesis (Schoch, 2003):

- All levels of repair operate 24 hours a day.
- A year, for the purpose of this simulation, is exactly 52 weeks long.
- Engines and modules are always repaired and never condemned.
- The D-Level repairs all modules, the I- Level does not.
- The I-Level assembles all engines, the D- Level does not.
- Engine repair at the I-Level begins as soon as there are enough modules to complete an engine.
- The O-Level has unlimited engine removal and installation capacity.
- The shipping times between the I and D-Levels are a constant.
- The O-Level removes an engine from a F/A-18 only for module failures and high times. All other maintenance requirements have a negligible effect on overall operational availability.
- F414-GE-400 engine failures are the result of independent failures of the modules in the engine.
- Once an F/A-18's flight schedule is set, the F/A-18 does not vary from it (except in the case of engine failure or high time because it is not flyable).
- If a F/A-18 experiences an engine failure, it lands immediately. No emergency diverts, aircraft lands back at base. The model assumes no return to origin delay.
- A F/A-18 may have both engines fail simultaneously.

2. Additional Assumptions

The simulation uses the following additional assumptions:

- The depot is assumed to have unlimited resources and therefore always has modules on hand ready for issue.
- The intricacies of the depot (e.g. man-hours) are not analyzed.
- There has been a recent push to privatize the Depot.
- Lockheed Martin will provide depot level support for the JSF under a Performance-Based Logistics (PBL) agreement.
- Because, a PBL agreement is to guarantee part delivery within a certain time, it is assumed assigning various values to the shipping time between the depot and the AIMDs captures the impact of depot level support.

- Upon repair, modules are good as new.
- For the ALS, an F/A-18's flight schedule is set, the F/A-18 does not vary from it (except in the case of detected pending engine failure or engine failure because it is not flyable).
- Once an RFI engine is installed in an aircraft, it is considered ready for normal flight. Functional check flights are not required.
- Cannibalization, taking parts off one aircraft to install in another is not an option.
- All aircraft enter service at the same time.
- All flights scheduled for 2.75 hours.

F. DATA

1. Data Source

The following data/values were obtained from Lieutenant Commander Schoch's (Schoch, 2003) thesis: module failure data, module high times, O and I level module engine removal, installation and inspection times, time to transfer engine from AIMD to squadron, number of squadrons and aircraft, and engine, module AIMD allowance. All values, except the module failure data, are listed in Appendix A.

2. Data Analysis of Module Time Between Failures

Text files containing time between failures data for each module type were analyzed. Using JMP statistical software, the Exponential, Weibull, Gamma, Normal, LogNormal and Beta distributions were fit to each module failure data. The Beta distribution is the best fit for each module type. The goodness-of-fit test yielded the following p-values:

- Module 1 (Fan) = 0.2500
- Module 2 (Compressor) = 0.2500
- Module 3 (Combustor) = 0.1820
- Module 4 (HPT) = 0.2500
- Module 5 (LPT) = 0.2500
- Module 6 (After Burner) = 0.2500

For each module type, evidence against the null hypothesis: Data is Beta distributed, is not significant.

G. CONCLUSION

The preceding section described the current, traditional logistic system which facilitates the F-414-GE-400 engine repair process. Then the F-414-GE-400 repair process was described under the ALS. The key components necessary to model the system are identified. The traditional logistic system and the ALS are different. The components and assumptions mentioned in this chapter are used to model the systems.

III. DISCRETE EVENT SIMULATION (DES) MODEL

Simkit event graphs aid in describing the simulation models for both the traditional and ALS systems. Event graphs also highlight the difference between the two models.

A. DES, EVENT GRAPHS AND SIMKIT

1. DES Paradigm

DES is a modeling paradigm in which the model's state remains constant except for particular events, which can take place at any place or time (Law and Kelton, 2000). Events are state transitions. The state of a system is the collection of variables necessary to describe the status of the system at any given time (Winston, 2004). The state changes at discrete points in time. Scheduled events are placed in a Future Event List (FEL) in chronological order. During the simulation, time is advanced in discrete steps to the next earliest event in the FEL.

2. Event Graphs

Event graphs are diagrams of physically representing discrete event simulation models (Buss, 2002). Events are represented by nodes. Directed edges are the scheduling relationship between pair of nodes. Nodes are the state transitions and arcs perform the scheduling. For the diagram below, if (i == true) then the occurrence of A causes the scheduling of B to occur after a delay of time t.

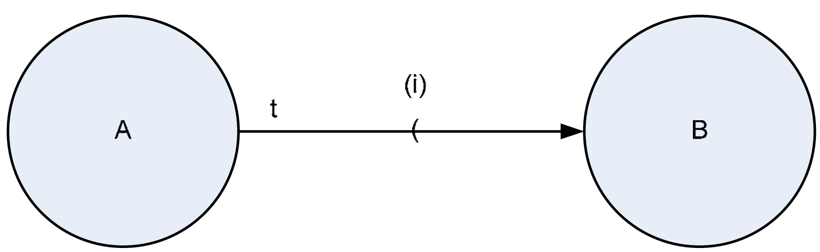

Figure 8. Event Graph Notation (From: Buss,2001,2)

3. Listener Pattern

A useful application in DES is the ability to make simulated components "listen" to another's events. When a scheduled event of the source component occurs, the event is simultaneously scheduled for all components listening to the source with the same event. In Figure 9 below, class B listens to class A. The arrival method in class B is scheduled by the self-scheduling arrival method of class A. For more information on DES and Simkit, see the reference (Buss, 2002).

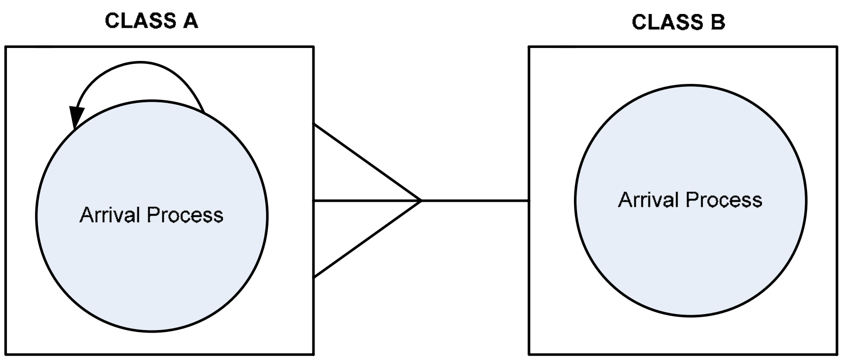

Figure 9. Class B 'Listens' to Class A

4. SimKit

All models in this chapter have been developed using Simkit. Simkit is a DES implementation software package written in Java, which directly supports building event graph models. Every event in an event graph model corresponds to an instance method in a Simkit class. The relationship between Simkit and event graph modeling is summarize in table 1. More information on how to use Simkit to create DES models can be found in (Buss, 2002). Simkit can be downloaded from the internet at the following URL: http://diana.or.nps.navy.mil/simkit/

Event Graph	Simkit
Parameter	Private instance variable, setter and getter
State Variable	Protected instance variable getter, no setter
Event	‘do’ method
Scheduling Event	Call to waitDelay() in scheduling event’s ‘do’ method
Run Event	Reset() method to initialize state variables; doRun() method to fire Property Change events for time-varying state variables
Events scheduled from Run event	Call to waitDelay() in doRun() method

Table 1. Relationship between Simkit and Event Graph modeling

B. DES MODEL FOR TRADITIONAL ENGINE REPAIR SYSTEM

As mentioned in chapter one, this thesis builds on Schochs’ thesis work. His model simulates the current/traditional F414-GE-400 engine repair process. The three levels of maintenance, O-level, I-level and D-level are represented. Simulates F/A-E/F flight schedules and engine failures are used to populate the engine process. The twelve Java classes of Schoch’s DES model follow with a brief description (Schoch, 2003).

1. Module Type Class

This class sets up the types of modules that can be used in a simulation. For the F414-GE-400 engine repair process simulation there are six types of modules.

2. Module Class

An object of this class represents a module. The module can be of any type specified by the module type class, for example: fan. A failure time is randomly selected from a data set corresponding to the module type. This object tracks component hours used and knows when it has reached high time or time of failure.

3. Engine Blueprint Class

This class details the specifications each engine must meet: position and type of each module, build window and high time schedule. O-Level engine removal,

installation and troubleshooting times are set in this class. Additionally, I-Level engine inspection time and module removal/installation time for each module type are set in this class.

4. Engine Class

An object of this class represents a F-414-GE-400 engine. It is made up of one of each type of module, for a total of six modules. It tracks engine hours and screens each module if it has reached high time or time of failure. The time to high time corresponds to the module time to high time with lowest value. The time to failure corresponds to the module failure with the lowest value. Each engine object must conform to the specifications of the Engine Blueprint class.

5. F18 Hornet Class

An object of this class represents an F/A-18E/F aircraft. The F/A-18E/F is simulated by using two engine objects and one FlightSchedule object. The aircraft object tracks its own hours. Time to high time corresponds to the engine time to high time with the lowest value. Time to failure corresponds to the engine time to failure with the lowest value. When an aircraft reaches time of failure of high time it is no longer flyable.

6. Flight Schedule Class

This class provides a selection of schedules an F/A-18E/F Hornet object. The schedules are arrays. Elements indexed by odd numbers in the array are ground times (time between flights). The even indexed elements in the array are flight times. The final odd placed element in the array is a zero. This element directs the F/A-18E/F Hornet to begin the flight schedule again.

7. O-level Class

An object of this class represents a squadron. When a supported aircraft reaches high time or has an engine failure, the squadron removes the engine. The squadron requests a replacement engine from its supporting I-level. Upon arrival, the replacement engine is installed in the aircraft by the O-level object.

8. I-level Class

An object of this class represents an AIMD. It delivers RFI engines to the O-levels it supports. A linked list keeps track of all good modules assembled on engines

awaiting part and in inventory. The best engines are built by screening and using modules with the largest amount of time remaining before high time is reached.

9. D-level Class

An object of the class represents a depot. Like an AIMD, the depot has linked lists which keep a track of all its modules. A module received from the AIMD is placed in the needs repair linked list.

10. F18 Simulation Manager Class

The entire infrastructure, setup in the F18 Simulation Setup class is created here. It determine out how many modules and engines are needed based on the number of aircraft and inventories at all I and D levels. This class keeps a record of every object made in the simulation and therefore serves as the report generator for the simulation.

11. F18 Simulation Randomness Class

All randomness in the simulation is generated in this class. Module times between failures are randomly selected, with replacement, from data that contains actual failure times.

12. F18 Simulation Setup Class

This class controls the entire simulation. This class is used to construct the infrastructure to be modeled in the simulation. The number of aircraft, squadrons, AIMDs, and I-level and D-level inventories are set up in this class. An entity knows what it supports because, using Simkit, it is registered to listen to it. Figure 10 shows the listening relationship between the object of each type class.

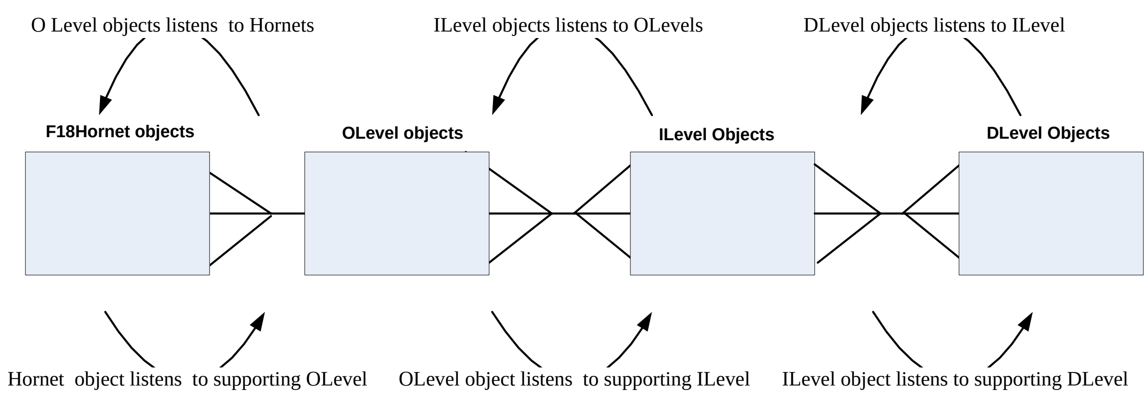

Figure 10. Listening Relationship of Simulated Objects

C. CHANGES TO SCHOCH'S MODEL

Two logistics systems are modeled: traditional and ALS. Schoch's simulation, with some adjustments, is used to model the traditional system. His simulation is altered for the ALS model. Differences for the traditional model include:

- For failure times, Schoch randomly selected failure times from data sets. In this thesis, a probability distribution is fit to each data set. These distributions are used to generate the failure times.
- Schoch modeled the depot in detail. This thesis has less depot detail. In this thesis, the depot has unlimited resources. Depot inventory levels and maintenance man hours are not considered in this thesis. Impact of depot level support is captured by assigning various values to the shipping time between the depot and AIMDs.
- Variables are added to the Schoch model to track squadron and AIMD man hours, number of requisitions made, number of requisition filled, number of requisitions gone off base, number of in-flight failures, and number of missions completed.

In addition to the differences above, for the ALS system changes to the Schoch model include:

- No high times.
- Prognostics (the ability to detect pending failures).

D. DES MODEL FOR ALS ENGINE REPAIR PROCESS

The model in this thesis simulates the F-414-GE-400 engine repair process in accordance with the ALS. The O-level and I-level are modeled with detail. The simulated F/A-18E/F aircraft are enhanced with prognostics. If an impending failure is detected, the aircraft send the information to each of the three levels of maintenance thereby initiating action at each level.

1. Engine Blueprint Class

As in the traditional model, all engines in the ALS must conform to the specifications detailed in the engine blueprint class. Prognostic accuracy and detection time before failure (lead time -remaining life after detection before the failure occurs) are set in this class.

2. F18 Hornet Class

The aircraft object keeps a track of its own flight hours. When the prognostics detect an impending failure, the O-level and I-level are instantly notified. Autonomously, a replacement engine is delivered to the squadron. The aircraft keeps making its scheduled flights until one of the following occur: the prognostic works properly and a replacement engine arrives, the prognostics works properly and the impending failure is predicted to occur during the next flight, or the prognostics do not work and an in flight failure occurs. The engine detection time check method screens for these events. The first two events result in the grounding of the aircraft. If the prognostics do not work and a failure occurs, then the ALS system responds in the same way as the traditional (Schoch) system. Additionally, a false positive time is generated for each aircraft object. When the aircraft reaches the false positive time, a module is randomly chosen for the prognostics detect an impending failure. The ALS F-18 Hornet event graph is displayed Appendix B.

3. O-Level Class

The O-level class keeps track of engine requests made from all the aircraft it supports. Additionally, it tracks maintenance hours. If the engine to be replaced has failed, the squadron responds in the traditional manner and begins troubleshooting. If the request was made by the ALS, the squadron does not troubleshoot the engine. The squadron waits until the replacement engine arrives then replaces the engine. The ALS O-level event graph is displayed in Appendix C.

4. I-Level Class

The I-level class keeps track of engine requests made from all the squadrons it supports. Additionally, it tracks the number of RFI modules ordered from and received from the depot. It also tracks its maintenance hours.

Engines received from the squadron have either failed or have an impending failure that has been detected. If an engine is received due to the prognostics, troubleshooting is not required. If a failed engine is received, troubleshooting is required.

Modules that have failed or those with detected impending failures are removed from the engine and sent to the depot for repair. In the case where module inventory is empty, additional modules may be removed from an engine in order to complete the

assembly of another engine. This practice is called cannibalizing. Cannibalizing is an allowed practice at the I-level. The ALS I-level Event graph is displayed in Appendix D.

5. D-level Class

The depot always has a replacement module always on hand. The level of service of the depot is captured by altering the I-level to D-level shipping times. The D-Level class keeps a track of the number of requisitions made to the depot. The D-Level Event graph is displayed in Appendix E.

6. Stochastic Class

Failures depend on module type. The probability distributions for module failures are set in this class. Additionally, the distribution that generates the false positive signals is set here.

E. CONCLUSION

DES models have been developed to simulate the traditional logistic system and the ALS. The characteristics and behavior of the system components are captured in the DES models. Java and Simkit are efficient tools in producing versatile models. Parameters can be changed easily to evaluate the systems. Modification can be made to the DES models to simulation other weapons platforms, specifically the JSF. However, before using the models, their validity needs to be determined. As a partial effort towards this, a stochastic model was formulated and compared with the simulation. This stochastic model is described in the following chapter.

IV. STOCHASTIC MODELS

Analytical models produce closed form expressions for MOEs. The use of an analytical model in the thesis is for comparison to the DES models. The results from the stochastic models are used to partially validate the DES models. The traditional and ALS systems can be modeled using stochastic models. The intent is not to assess the entire logistic processes using stochastic models. Aircraft engine time between failures and repair times are used to approximate the long run average rate of failure and the operational availability of the engine. The long run average rate of failure is the *number of failures per flight hour* (FPF). The operational availability is the long run proportion of time the aircraft is up. The I level and the D level are not captured in the stochastic models. The output of the DES model and the stochastic model results are compared under the same model assumptions.

A. ASSUMPTIONS AND DES MODEL

Each modular lifetime distribution is assumed to be exponentially distributed with a mean of 1,000 hrs. Repair time of an aircraft is constant. If a failure occurs, repair time is three hours. If prognostic detects the impending failure, repair time is two hours. The additional hour of repair is added for a failure because trouble shooting is required to isolate the problem. A repair returns the aircraft to as good as new.

The parameters listed above are used in the DES models are set to the above values. The stochastic models assume a system (aircraft) has two modes: in-use or not-in-use. System modes are set to in-use until a failure occurs. During repairs, systems are in-use. After the repairs are complete, systems return to the in-use mode. The DES models are modified to represent this assumption for comparison with the stochastic analytical models. For comparison runs only, aircraft are scheduled for a single long flight. A two-year flight duration is used as an arbitrarily large value. The flight is only interrupted if a failure occurs and or an impending failure is detected. Immediately upon repair the aircraft continues its mission. Each simulation run is replicated 100 times.

Each DES model result is the mean of the 100 replications. A discussion of sample size selection is included in section D of Chapter V.

B. RENEWAL PROCESS

1. Module Failures Process as a Renewal Process

First, a renewal process is defined, and then counting the number of module failures is shown to satisfy the definition.

> If the sequence of times between events $\{X_1, X_2 ...\}$ is independent and identically distributed, then the counting process $\{N(t),\ t \geq 0\}$ is said to be a renewal process (Ross, 2003).

The nonnegative variables denote the time between the (n-1)st and nth events. An event is a renewal. Consider a module, time between module failures is nonnegative and independent and identically distributed. Therefore, counting the times a module fails is a renewal process. In addition, allowing the module failures to be exponentially distributed makes the process a Poisson process. The Poisson process has unique properties which make formulation easier. The rate of a Poisson process is $\lambda = \frac{1}{mean}$.

2. Aircraft Failures as a Poisson Process

An F-18/A aircraft has two engines. Each engine has twelve modules. The aircraft engine failure process is the sum of the twelve independent module failure Poisson processes. The sum of independent Poisson processes is a Poisson process with a rate equal to the sum of the rates of the independent processes (Ross, 2003).

As a result: $\lambda = \lambda_1 + \lambda_2 + .. + \lambda_{12} = \frac{12}{1000} = 0.012$. Where: λ is the rate of failure of an aircraft, λ is the rate of the nth module and $\lambda_1 = \lambda_2 = .. = \lambda_{12} = \frac{1}{1000}$.

3. Long Run Average Failure Rate

The average rate of a renewal process converges to the reciprocal of the expected value of time between two consecutive events as time approaches infinity.

$$\frac{N(t)}{t} \rightarrow \frac{1}{E[X]} \text{ as } t \rightarrow \infty \text{ (Ross, 2003)}$$

For the Poisson process, inter arrival times are exponentially distributed. The expected value of the exponential process is the reciprocal of its rate λ. Therefore, the long average rate of a Poisson process is $1/(1/\lambda) = \lambda$.

4. The Aircraft Repair Process as a Renewal Process

Formulation of the failures is already developed in part three of this section. However the aircraft is also subject to repair. Repair times are assumed constant and are independent and identically distributed. Let $R(t)$ be the number of repair completions and let c be the repair time. $R(t)$ is a renewal process. For the model the expected time between repair completions is $\lambda + c$.

5. The Renewal Reward Process and Long Run Average Availability

For a renewal process, suppose at each interarrival time X a reward is received. Let A be the reward received at each renewal. Let $Z(t)$ represent the total reward earned by time t. $Z(t)$ is called a renewal reward process.

The $\lim_{t\to\infty} \frac{Z(t)}{t} = \frac{E[A]}{E[X]}$ (Ross, 2003). In other words, the long run average rate of renewal reward process is the expected amount of reward per cycle divided by the length of the cycle. As a result the long run average rate of availability is the expected time a device is up in a cycle divided by the expected length of the cycle (Jacobs, 2006). For our model this translates to: long run average rate of availability is $\frac{\lambda}{\lambda + c}$.

C. VALIDATING THE TRADITIONAL SYSTEM

The traditional system enforces an age replacement policy. Modules are replaced upon failure or upon reaching a predetermined age.

1. Age Replacement Policy and Long Run Average Failure Rate

For a Poisson process, the long run average failure rate for the age replacement policy is the same as the long run average failure rate as replacing components only upon failure. A proof of this statement is provided in Appendix F.

The long average rate of failure is: $\lambda = \frac{12}{1000} = 0.012 / \mathit{flighthour}$.

The traditional DES model yields: $0.01094 \quad \text{standard error} = 0.0003$.

The relative difference is: $\frac{|0.012 - 0.01094|}{0.012} = 8.8\%.$

2. Long Run Portion of Time an Aircraft is Up

The expected time between failures is $\frac{1}{\lambda} = \frac{1000}{12}$. The expected repair time is three hours. The expected time between repair completions is: $\frac{1000}{12} + 3$.

The long run availability rate is: $\frac{1000}{12} / (\frac{1000}{12} + 3) = 0.9653$.

The traditional DES model yields: $0.9682 \quad \text{standard error} = .001$.

The relative difference is $\frac{|0.9653 - 0.9682|}{0.9653} = 0.3\%.$

D. VALIDATING THE ALS

Up to this point, the traditional system has been discussed. Changes to the traditional stochastic model are made to account for the detection capabilities of the ALS. If prognostics work the impending failure is detected and the module is replaced before failure. If the prognostics do not work the module fails.

The counting of module failures occur is a Poisson process with rate λ. The ALS model is as follows. Each failure is associated with an independent trial. If the prognostics work the trial is a success. Let p be the prognostic accuracy, then the probability of success is p. The probability of a failure, the prognostics did not work, is $1 - p$. Let $L(t)$ be the number of failures, then $L(t)$ is a Poisson process with rate $\lambda \times (1 - p)$ (Jacobs, 2006).

1. Long Run Average Failure Rate

Let $p = 0.9$, then the long run average failure rate is $\frac{12 \times (1 - 0.9)}{1000} = 0.0012$.

The ALS model yields: $0.00138 \quad \text{standard error} = .00196$.

The relative difference is: $\frac{|0.0012-0.00138|}{0.0012}=15\%.$

2. Long Run Average Availability Rate

The expected time between failures is $\frac{1}{\lambda}=\frac{1000}{12}$.

The expected repair time is $(3\times(1-p))+(2\times p)$.

The expected time between repair completions is $\frac{1000}{12}+(3\times(1-p))+(2\times p).$

Let $p=0.9$, then the long run average failure rate is:

$$(\frac{1000}{12})/(\frac{1000}{12}+(3\times(1-p))+(2\times p))=0.997486.$$

The ALS DES model yields: $0.9956 \quad \text{standard error} = .00057$.

The relative difference is: $\frac{|0.997486-0.9956|}{0.997486}=0.18\%.$

E. CONCLUSIONS

The stochastic models are simple and can be used to provide a solution quickly. However, stochastic models are low resolution. Stochastic models capture the general overall behavior of the logistic system and are used to checked higher resolution simulation models. The simulation models pass face validation. Although this does not constitute a complete validation of the DES models, matching the analytical results gives confidence to the DES models' correctness. The DES models are required to study the entire engine process in detail. The next step is to simulate the traditional and logistic system using the DES models.

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V. RESULTS AND DISCUSSION

This chapter discusses data generation, MOEs and design factors. A Latin Hypercube design is used to derive maximal information in a reasonable number of runs. Simulation input and output for both the traditional system and the ALS is also addressed.

A. DESIGN OF SIMULATION EXPERIMENTS

1. Measures of Effectiveness

Within the DOD**,** the most common MOE for aircraft readiness is operational availability. Operational availability is analyzed as a response variable. However, operational availability can be misleading. Operational availability does not indicate how often aircraft are used or how often they fail. If a squadron with flyable aircraft did not fly for a year, the operation availability for the year is 100%. In this instance, no conclusions can be made about the logistic system in place. Other indictors also should to be considered in order to get a more accurate picture of the logistic system.

Other MOEs or response variables considered are: MMHF and FPM. FPM is not the same as FPH, which was used in the previous chapter. Both of these response variables are directly proportional to cost and provide insight to the effectiveness of allocating parts and personnel.

2. Design Factors

Design factors are the independent variables considered as predictors for the MOEs. The traditional system has four design factors: module reliability, build window, depot-turn-around-time and inventory levels. The ALS system has six design factors: module reliability, detection lead time, prognostic accuracy, false positive rates, depot turn around times and inventory levels. The design factors are analyzed to determine their influence on each of the MOEs.

The baselines for both logistic systems used to compare all results are listed in Table 6 of Appendix A. The design factors and the values they can take are summarized in Table 2 below. Module reliability is increased by increasing the mean of each

distribution. Inventory levels for each module are simultaneously increased with values from the table. Detection lead time is the amount of life remaining on a module once an impending failure is detected. False positive rates are exponentially distributed with the mean values indicated in Table 2.

Design Factor	**Values**
Module reliability (hrs)	0,100,200,300,400,500,600,00,800,900,1000
Build Window (hrs)	50, 100, 150, 200,250,300,350,400,450,500
Depot Turn Around (days)	5,10,15,20,25,30,35,40
Detection Lead Time (hrs)	15,20,25,30,35,40
Prognostic Accuracy	0.90,0.91,0.92,0.93,0.94,0.95,0.96,0.97,0.98,0.99,1.0
False Positive Means (hrs)	450, 500,550,600,650,700
Inventory (modules)	0,1,2,3,4,5,6,7,8,9,10

Table 2. Design Factors and Ranges

A common technique in experiment design is to run the model using a baseline, additional runs are made changing one design factor/predictor variable at a time. Predictor variables with the greatest impact are then selected as significant factors. This approach is incomplete because: significant combinations of design factors may be overlooked. For the full factorial design, adding more design factor levels results in numerous required simulation runs. Fractional factorial designs reduce the number of runs, but introduce confounding of interactions between design factors. Key interactions may be masked or confounded by the main effects (first order effects).

3. Latin Hypercubes

A full factorial design considers factor interactions. Such a design for all combinations of the four predictor variables for the traditional model would require 9,680 design points. A full factorial design of all combinations of the six predictor variables for the ALS model would require 383,328 design points. Fortunately, other methods can be used to construct valid confidence estimates for the MOEs with fewer design points.

Latin Hypercubes are a very good all-purpose design, particularly when factors are quantitative because of: efficiency, space-filling, design flexibility, and analysis flexibility (Sanchez, 2006). The nearly-orthogonal Latin Hypercube (NOLH) design is used for this experiment. A spreadsheet written by Professor Susan Sanchez, Naval Postgraduate School, was used to generate seventeen design points for each system.

B. SIMULATION INPUT AND OUPUT

The model input and outputs are summarized in Table 3 and Table 4. Table 3 refers to the traditional model. Table 4 refers to the ALS model. The inputs are the design factors. The outputs are the MOEs. Each row is a design point (simulation run) with its corresponding output. Each simulation run is replicated 100 times. The corresponding output is the mean of the 100 replications. The following section is a discussion of the sample size detection.

Traditional Model

Input				Output		
Reliability (hrs)	Depot (days)	Inventory (modules)	Build (hrs)	Availability	FPM	MMHF
400	960	8	200	0.9962	0.0176	0.3702
200	360	9	300	0.996	0.0207	0.3956
200	480	1	150	0.9956	0.0206	0.4202
300	600	3	500	0.9965	0.0191	0.3664
800	960	4	100	0.9955	0.0133	0.3504
1000	360	4	400	0.9964	0.0123	0.2826
700	240	10	200	0.9967	0.0143	0.3288
600	840	8	450	0.997	0.0155	0.3163
500	600	5	300	0.9966	0.0165	0.3405
700	120	2	350	0.997	0.0145	0.3097
900	720	1	250	0.9953	0.0128	0.3032
900	600	9	400	0.9965	0.013	0.2888
800	480	7	500	0.9971	0.0138	0.2936
300	120	6	450	0.9964	0.0192	0.3676
100	720	6	150	0.9954	0.0223	0.443
400	840	0	350	0.9965	0.0178	0.3577
500	240	3	100	0.996	0.0162	0.3818
Depot = depot turn around time (days)						

Table 3. Traditional System Input and Output

ALS

Input						Output		
Reliability (hrs)	Depot (days)	Inventory (module)	Prognostics (fraction)	False (hrs)	Lead (hrs)	Availability	FPM	MMHF
300	40	8	0.94	500	40	0.997	0.0011	0.266
100	15	9	0.96	450	25	0.9966	0.0009	0.306
100	20	1	0.93	600	35	0.9966	0.0017	0.3108
200	25	3	1	600	20	0.9969	0	0.2753
800	40	4	0.91	550	15	0.9978	0.0012	0.1976
1000	15	4	0.98	450	35	0.998	0.0002	0.177
600	10	10	0.93	650	25	0.9975	0.0011	0.2183
600	35	8	0.99	650	30	0.9976	0.0002	0.2136
500	25	5	0.95	600	30	0.9974	0.0008	0.2296
700	5	2	0.96	650	15	0.9977	0.0005	0.2044
900	30	1	0.94	700	30	0.9979	0.0007	0.1867
900	25	9	0.98	550	20	0.9979	0.0002	0.1853
800	20	7	0.9	550	35	0.9978	0.0013	0.1995
300	5	6	0.99	600	40	0.9971	0.0002	0.2587
0	30	6	0.92	700	20	0.9995	0.0016	0.3057
400	35	0	0.97	500	30	0.9972	0.0005	0.2439
400	10	3	0.91	500	25	0.9973	0.0016	0.2481

F= False positive rate
Depot = Depot turn around time
Lead = Detection Lead Time

Table 4. ALS Model Input and Output

C. POWER ANALYSIS AND SAMPLE SIZE SELECTION

Power analysis is used to determine sample size (number of replications required) based on a β (probability of a type II error) of 0.1. Power is 1- β which is 0.9. The (probability of a type I error), α, is set to 0.05. The model being evaluated is: Response variable = (true mean) + (factor effect) + (error). If the null hypothesis is true, then the factor effect is zero. The sample size required to detect a deviation in the true mean due to a non-zero factor effect is determined. To detect a smaller effect a larger sample size is required.

JMP statistical software is used to calculate the power curve. An estimate of standard deviation is needed to perform the calculation. Standard deviation is estimated by repeating each design point 100 times and calculating sigma-hat. Figure 11 is generated to determine the sample size for operational availability in the traditional

logistic model. The graph is a 0.9 power curve. For deviations of 0.005, 45 replications are needed to detect that deviation with a probability of 0.90.

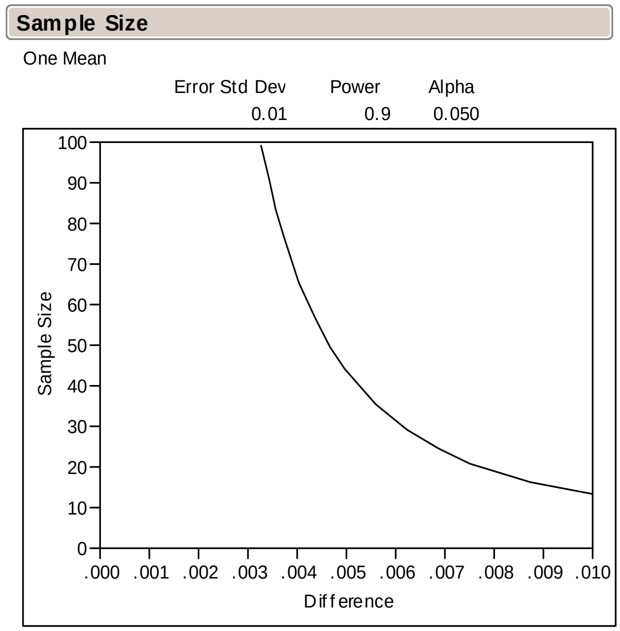


Figure 11. 0.9 Power Curve

A 0.90 power curve is computed for each MOE in each model by using the same procedure. The results are summarized in table 5. All effects detected are smaller than 0.008. The largest n required is: 70. With 100 replications smaller deviations can be detected with a power of 0.90.

	Traditional Logistic System		**ALS**	
	sample size	**deviation**	**sample size**	**deviation**
Operational	45	0.005	60	0.005
FPF	45	0.0015	70	0.0075
FPM	45	0.0020	60	0.005
MMHF	60	0.0020	60	0.006

Table 5. Power Analysis results.

D. ANALYSIS OF THE SIMULATION OUTPUT

Each simulation produces three output MOEs. Analysis of the MOEs for both the ALS and traditional logistic system served to compare both models.

The intent of the simulation is to study the effects of the design factors on each of the MOEs. To gain insight into the relationship of the variables, linear regression models are fitted to the generated data. The regression models are a result of using stepwise regression and residual analysis. The stepwise algorithm adds and drops terms by using the Akaike's Information Criterion. The P-value is the probability the effect of a variable equals zero. Variable with P-value greater then 0.001 are not considered. The smaller the P-value the more evidence there is against the null hypothesis: the predictor variable has no effect. If diagnostic plots do not support the modeling assumptions of normal errors and homoscedasticity, mathematical transformations are applied until the assumptions are satisfied. Transformations include: logarithmic, reciprocal, arcsine and square root. Additionally, if the relationship between the response variable and the predictor variables is not linear, polynomials of degree two are used for the regression.

JMP statistical software is used to perform multiple regression and to generate graphs to summarize the analysis. For each MOE, linear regression models are produced to describe its relationship with the input variables of each system. Scatter plot matrices are used to check the pairwise relationship between all variables. When two or more predictor variables are found to be significant a correlation matrix is generated to verify they are independent. Contour plots are used to compare the value of predictor variable pairs for an MOE. The contour values are plotted from the results of the 17 design points. The contour plot is not a feasible region and it may or may not contain the optimum point.

The predictive capability of each model is verified by exploring inputs not already used. A specific combination of design factors yields the optimal value for each MOE. An optimal solution is sought for each MOE: maximum operational availability, minimum FPM and maximum MMHF. The optimal solution is found for each linear model. The DES model is then run with the optimal solution. The output generated by inputs for the DES model and linear model are compared. Outputs close in value indicate

an adequate linear model. It is important to note the linear models are valid for specific predictor variable ranges. Values outside the define ranges from table 2 are not explored.

A linear model with predictive capability can provide as much insight as the more computationally intensive DES model. Additionally, a linear model can be put in an Excel spreadsheet which is easier and quicker to use. For FPM and MMHF, linear models are be used to compare the traditional system and the ALS.

1. Traditional Repair System

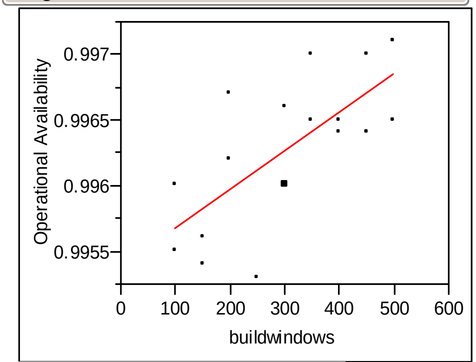
Data generated by the DES traditional repair system model resulted in good predictive models for FPM and MHPF, but not for operational availability.

a. Operational Availability

Regression is used to fit a linear model to explain the relationship between the predictor variables: module reliability, build window, depot turn around time, and inventory, and the response variable operational availability. Figure 12 is the JMP regression report. The parameter estimates table of the report gives the estimated coefficients, their standard errors and the corresponding t-statistics to test the partial effect of each variable. The R^2 for this least square fit is 0.503, indicating the regression model does not adequately explain the variation in operation availability. Build windows is the only predictor variable kept in the model. Inventory and depot turn around time were anticipated to be significant in terms of operational availability. Not being selected for the model does not mean they are not important. For the predictor variable ranges from table 3, inventory and depot turn around time do not limit operational availability. For the traditional logistic system, I-level inventory equivalent to that from table 6 with a guaranteed depot turn around time of 40 days is all that is required. In other words, once at this level increasing the I-level inventory or decreasing the depot turn around time has a minimal effect on operational availability. At this level, the main driver for operational availability is build windows.

Response Operational Availability

Regression Plot



Summary of Fit

RSquare	0.503204
RSquare Adj	0.470084
Root Mean Square Error	0.000412
Mean of Response	0.996276
Observations (or Sum Wgts)	17

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Ratio
Model	1	0.00000258	0.0000026	15.1935
Error	15	0.00000255	1.6992e-7	Prob > F
C. Total	16	0.00000513		0.0014

Lack Of Fit

Source	DF	Sum of Squares	Mean Square	F Ratio
Lack Of Fit	7	0.00000161	2.2984e-7	1.9561
Pure Error	8	0.00000094	1.175e-7	Prob > F
Total Error	15	0.00000255		0.1836
				Max RSq
				0.8168

Parameter Estimates

Term	Estimate	Std Error	t Ratio	Prob>|t|
Intercept	0.9953838	0.00025	3983.5	<.0001
buildwindows	0.0000029	7.559e-7	3.90	0.0014

Effect Tests

Source	Nparm	DF	Sum of Squares	F Ratio	Prob > F
buildwindows	1	1	0.00000258	15.1935	0.0014

Figure 12. JMP Regression Report for Traditional System Operational Availability

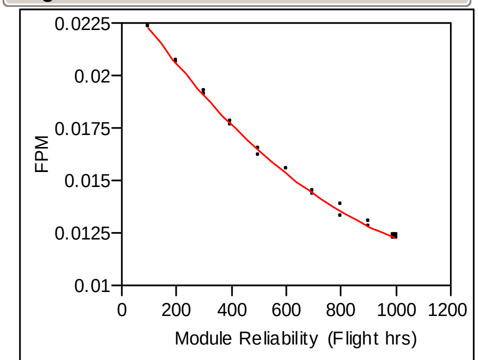
b. Failures Per Flight Mission

Regression is used to fit a linear model to explain the relationship between the predictor variables: module reliability, build window, depot turn around time and inventory, and the response variable FPM. Figure 13 is the JMP regression report. R^2 for this least square fit is 0.998, indicating the regression does a good job in accounting for the variability in FPM. The parameter estimates table of the report gives the estimated coefficients, their standard errors and the corresponding t-statistics to test the partial

effect of each variable. Module reliability is the only predictor variable selected for the linear model. Build windows is the next significant variable, but not significant enough to be included in the model.

Response FPM

Regression Plot



Summary of Fit

RSquare	0.998113
RSquare Adj	0.997844
Root Mean Square Error	0.000145
Mean of Response	0.016441
Observations (or Sum Wgts)	17

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Ratio
Model	2	0.00015573	0.000078	3703.262
Error	14	0.00000029	2.103e-8	Prob > F
C. Total	16	0.00015602		<.0001

Lack Of Fit

Source	DF	Sum of Squares	Mean Square	F Ratio
Lack Of Fit	7	5.43588e-8	7.7655e-9	0.2265
Pure Error	7	0.00000024	3.4286e-8	Prob > F
Total Error	14	2.94359e-7		0.9657
				Max RSq
				0.9985

Parameter Estimates

<table>
<tr><th>Term</th><th>Estimate</th><th>Std Error</th><th>t Ratio</th><th>Prob>|t|</th></tr>
<tr><td>Intercept</td><td>0.0220116</td><td>0.000088</td><td>250.42</td><td><.0001</td></tr>
<tr><td>Module Reliability (Flight hrs)</td><td>-0.000011</td><td>1.302e-7</td><td>-85.51</td><td><.0001</td></tr>
<tr><td>(Module Reliability (Flight hrs)-547.059)*(Module Reliability (Flight hrs)-547.059)</td><td>7.1084e-9</td><td>5.52e-10</td><td>12.87</td><td><.0001</td></tr>
</table>

Effect Tests

Source	Nparm	DF	Sum of Squares	F Ratio	Prob > F
Module Reliability (Flight hrs)	1	1	0.00015375	7312.29	<.0001
Module Reliability (Flight hrs)*Module Reliability (Flight hrs)	1	1	0.00000348	165.5464	<.0001

Figure 13. JMP Regression Report for Traditional System FPM

The scatter plot matrix, Figure 14, indicates there is no collinearity between module reliability and build windows. The plot shows a linear relationship between module reliability and FPM. This supports the fitted model: $0.022-(0.00001*\text{ModuleReliability})+(0.00000007*(\text{ModuleReliabilty}-547.06)\text{^}2)$

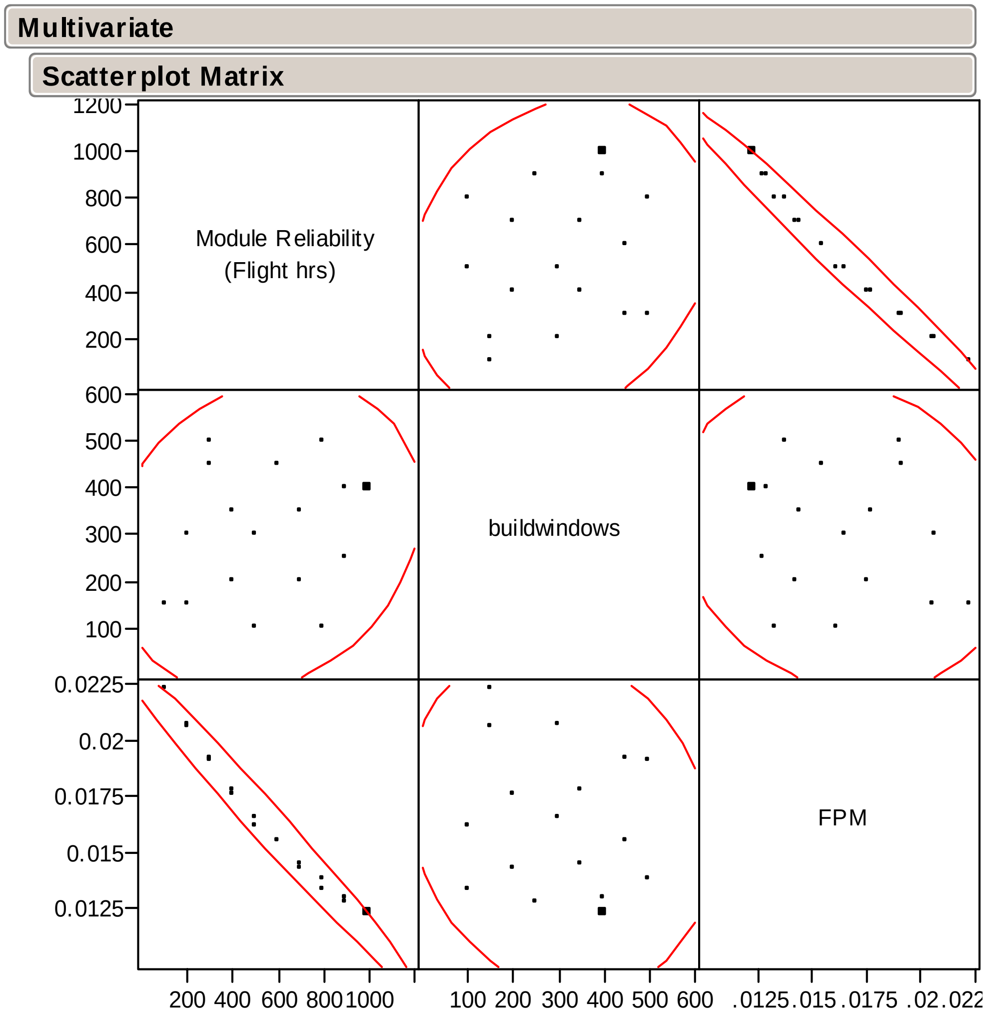


Figure 14. Scatter Plot Matrix Traditional System FPM

Figure 15 is a contour plot, comparing module reliability and build windows in terms of FPM. The vertical color shading pattern suggests failure rate improves with the increase of module reliability and is not affected by build windows. This provides further support for the fitted model.

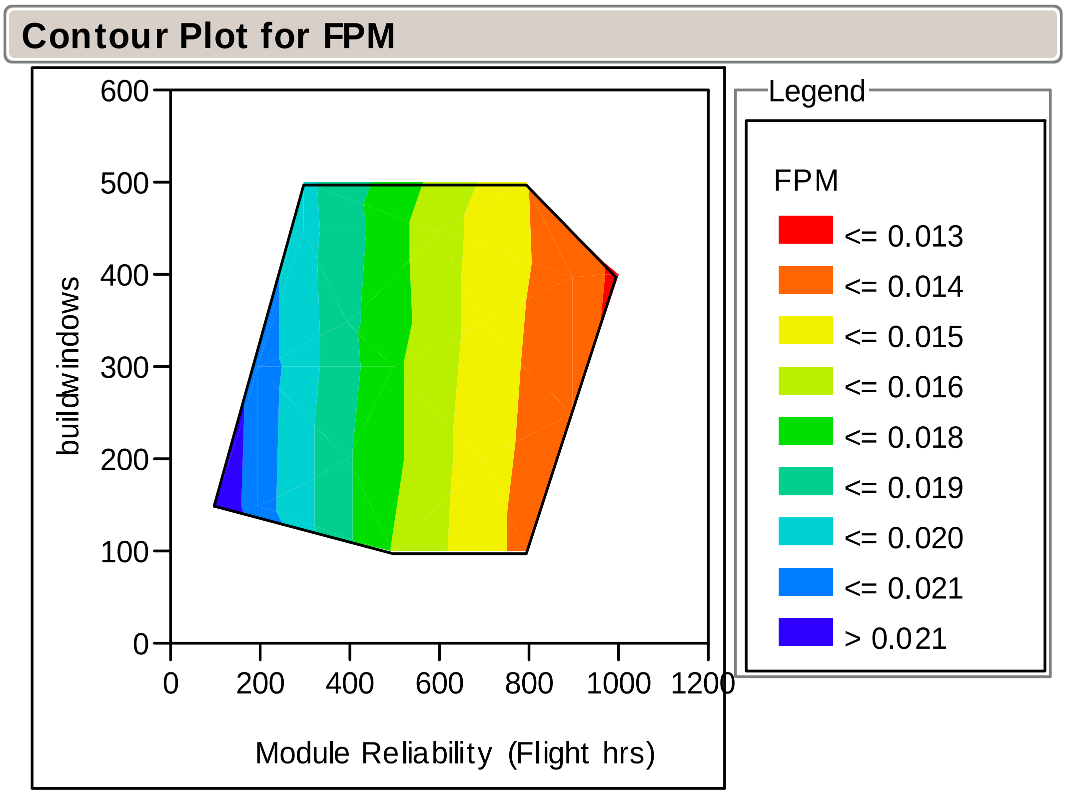


Figure 15. Contour Matrix Traditional System FPM

Figure 16 is a plot of the FPM linear model of the traditional logistic system over the module reliability range. The fitted regression model decreases in FPM when module reliability increases. Therefore, the largest value of module reliability in the model range produces the smallest FPM. The highest value of the module reliability is 1000 hrs. Module reliability is set to 1000 hrs. The regression model produces an FPM of 0.01234. With module reliability fixed at 1000 hrs, the DES model for the traditional repair system produces an FPM of 0.0125 with standard error 0.00004. The difference between the regression model and the simulation model is 1.28 %.

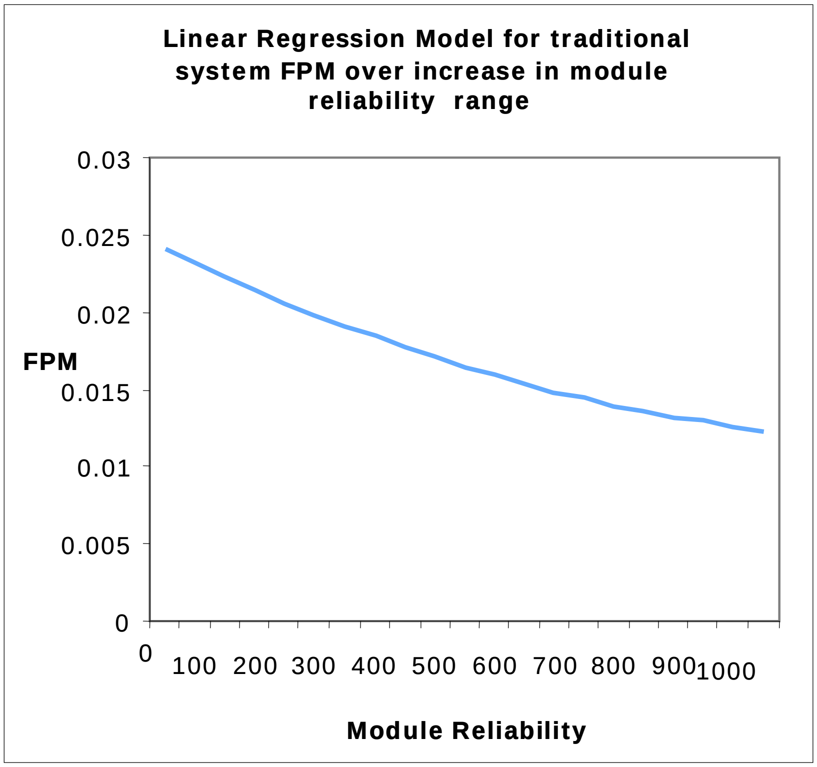


Figure 16. FPM Linear Regression Model for Traditional Repair System

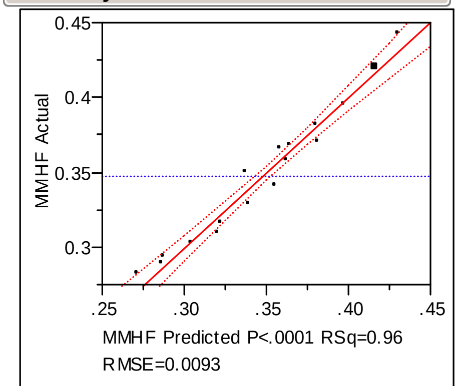
c. Maintenance Man Hours Per Flight Hour

Regression is used to fit a linear model to explain the relationship between the predictor variables: module reliability, build window, depot turn around time and inventory, and the response variable MMHF. Figure 17 is the JMP regression report that includes a correlation matrix.. R^2 is 0.964, indicating the regression does a good job in accounting for the variability in MMHF. The parameter estimates table of the report gives

the estimated coefficients, their standard errors and the corresponding t-statistics to test the partial effect of each variable. Module reliability and build windows are the predictor variables selected for the linear model. Module reliability and build windows have approximately equal weight on the expected value of MMHF.

Response MMHF

Actual by Predicted Plot



Summary of Fit

RSquare	0.964953
RSquare Adj	0.959946
Root Mean Square Error	0.009308
Mean of Response	0.348024
Observations (or Sum Wgts)	17

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Ratio
Model	2	0.03339347	0.016697	192.7328
Error	14	0.00121284	0.000087	Prob > F
C. Total	16	0.03460631		<.0001

Parameter Estimates

Term	Estimate	Std Error	t Ratio	Prob>|t|
Intercept	0.4632566	0.006733	68.81	<.0001
Module Reliability (Flight hrs)	-0.000141	0.000008	-16.59	<.0001
buildwindows	-0.000126	0.000017	-7.24	<.0001

Effect Tests

Source	Nparm	DF	Sum of Squares	F Ratio	Prob > F
Module Reliability (Flight hrs)	1	1	0.02384449	275.2404	<.0001
buildwindows	1	1	0.00454368	52.4484	<.0001

Correlation of Estimates

Corr

	Intercept	Module Reliability (Flight hrs)	buildwindows
Intercept	1.0000	-0.5456	-0.6536
Module Reliability (Flight hrs)	-0.5456	1.0000	-0.1853
buildwindows	-0.6536	-0.1853	1.0000

Figure 17. Traditional MMHF Regression Model

The scatter plot matrix, Figure 18, indicates there is no collinearity between module reliability and build windows. The plot shows a moderate linear relationship between build windows and MMHF. However, the plot shows a slightly stronger linear relationship between module reliability and MMHF. This supports the fitted regression model: $0.46 - (0.00014 * \text{reliabilty}) - (0.000125 * \text{buildwindow})$.

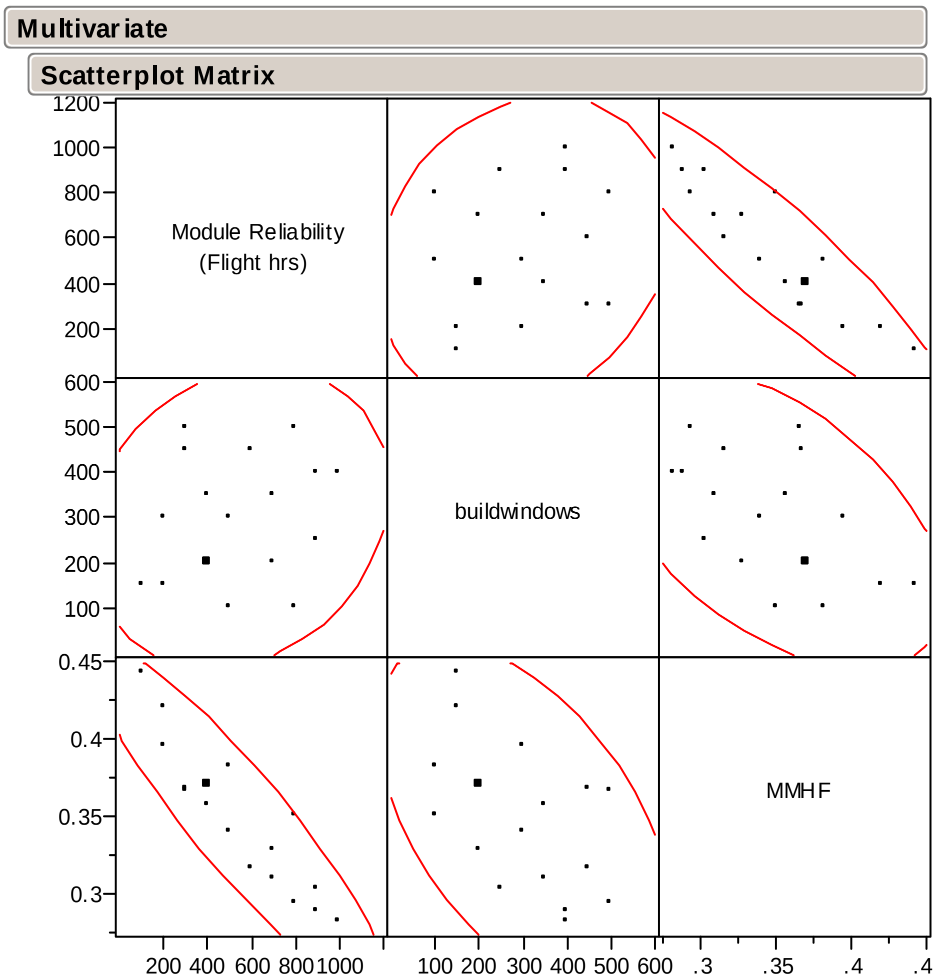


Figure 18. Scatter Plot Matrix Traditional System MMHF

Figure 19 is a contour plot, comparing module reliability and build windows in terms of MMHF. The color shading forms a forty-five degree pattern suggesting module reliability and build windows are nearly equivalent predictors of MMHF. This provides further evidence in support of the fitted regression model. Additionally, build window has no effect on MMHF when module reliability is 800 hrs or greater.

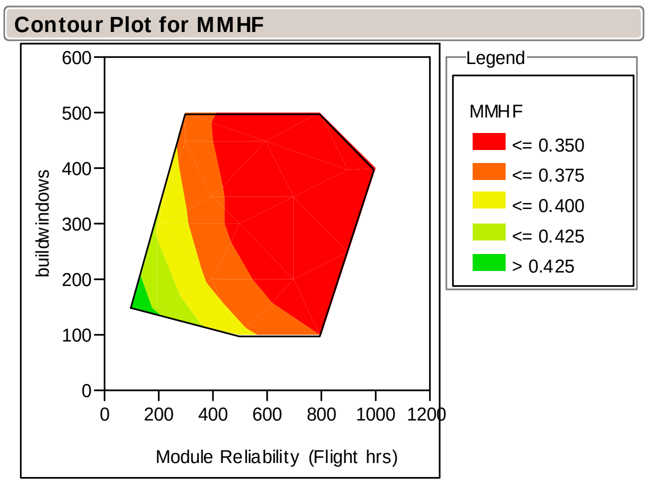


Figure 19. Contour Plot Traditional System MMHF

Figure 20 is a plot of the MMHF linear model of the traditional repair system over the build window range with no improvement in module reliability range. Figure 21 is a plot of the MMHF linear model of the traditional repair system over the module reliability range and a constant build window of 500 hours. The fitted regression model predicts a decrease in MMHF when module reliability increases or when build window increases. Linear programming is used to optimize the MMHF regression model with the predictor variable ranges as constraints. Setting both module reliability and build window to the highest value in their respective range yield the optimal (smallest) MMHF. Module reliability is set to 1000 hrs and build window is set 500 hours. The regression model produces an MMHF of 0.2954. The DES model for the traditional repair system produces an MMHF of 0.2755 with standard error 0.000047. The difference between the regression model and the simulation is 7.2%.

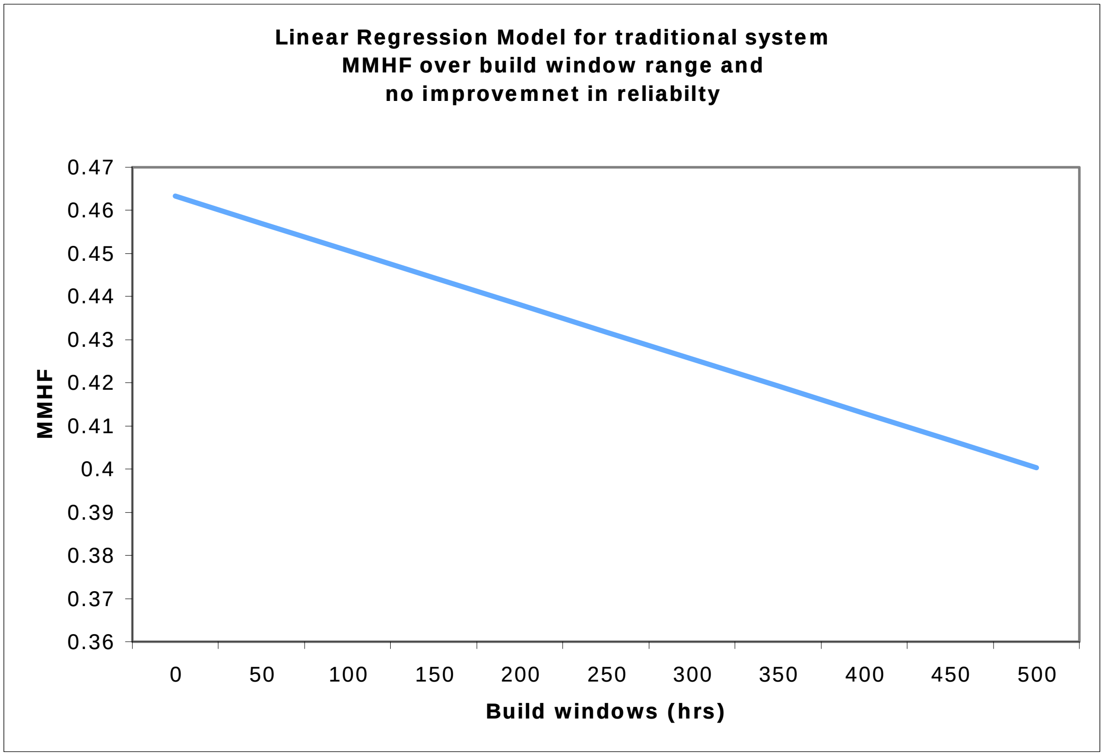


Figure 20. MMHF Regression Model for Traditional Repair System

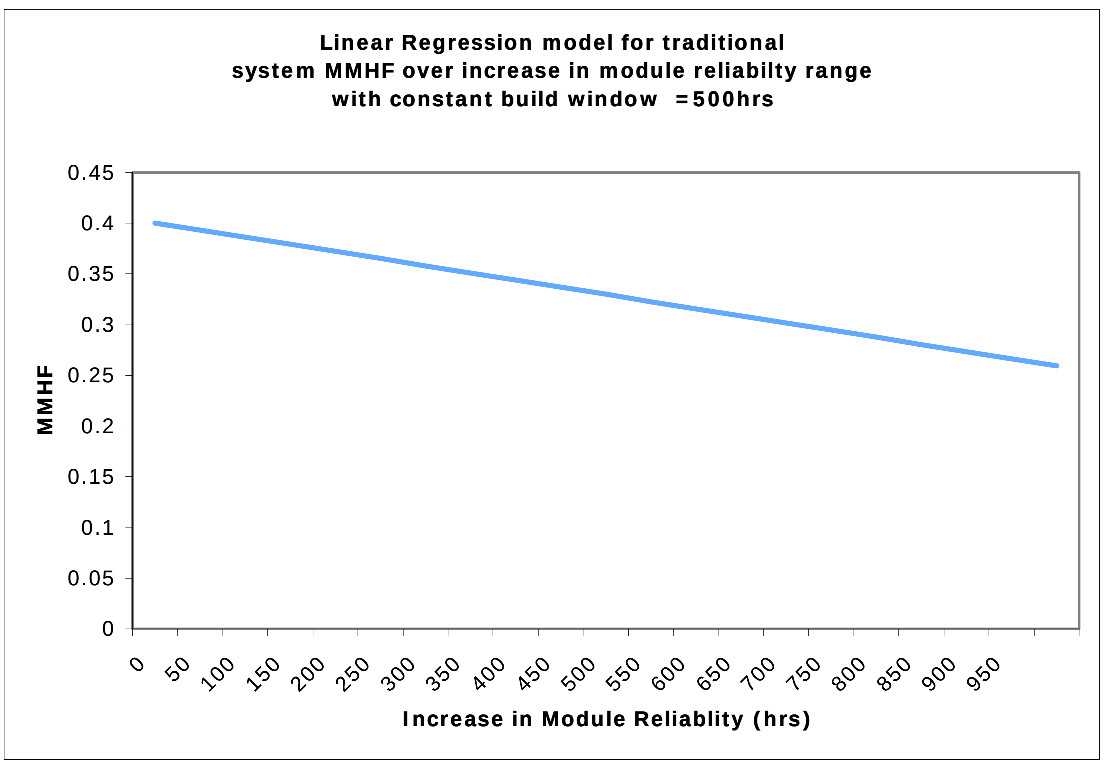


Figure 21. MMHF Regression Model for Traditional Repair System

2. Analysis of ALS Output

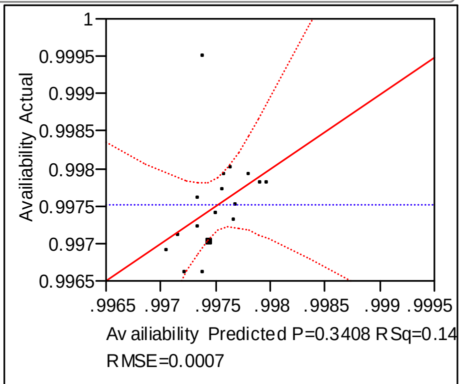
Data generated by the DES ALS model resulted in good predictive models for the FPM and MMHF but not for operational availability.

a. Operational Availability

Regression is used to fit a linear model to explain the relationship between the predictor variables: module reliability, prognostics accuracy, false positives, depot turn around time, inventory and detection lead time, and the response variable operational availability. Figure 22 is the JMP regression report. The parameter estimates table of the report gives the estimated coefficients, their standard errors and the corresponding t-statistics to test the partial effect of each variable. The R^2 value is 0.14, indicating the linear regression model does not explain the variation in operation availability. This suggests the selected multiple regression model predicts poorly. Module reliability and prognostic accuracy are the only predictor variables kept in the model. Inventory and depot turn around time were anticipated to be significant in terms of operational availability. Not being selected for the model does not mean they are not important. For the specific variable ranges from table 4, inventory and depot turn around time do not limit operational availability. For the ALS, I-level inventory equivalent to that from table 6 with a guaranteed depot turn around time of 40 days is all that is required. In other words, at these specific values increasing the I-level inventory or decreasing the depot turn around time has a minimal effect on operational availability. At these specific values, the main driver for operational availability is prognostic accuracy followed by module reliability.

Response Availiability

Actual by Predicted Plot



Summary of Fit

RSquare	0.142536
RSquare Adj	0.020041
Root Mean Square Error	0.00067
Mean of Response	0.997518
Observations (or Sum Wgts)	17

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Ratio
Model	2	0.00000104	5.2202e-7	1.1636
Error	14	0.00000628	4.4862e-7	Prob > F
C. Total	16	0.00000732		0.3408

Parameter Estimates

Term	Estimate	Std Error	t Ratio	Prob>|t|
Intercept	1.0025573	0.005092	196.88	<.0001
Module Reliabilty (flight hrs)	5.9124e-7	5.347e-7	1.11	0.2874
Prognostics Accuracy (%)	-0.005616	0.005347	-1.05	0.3113

Effect Tests

Source	Nparm	DF	Sum of Squares	F Ratio	Prob > F
Module Reliabilty (flight hrs)	1	1	5.48618e-7	1.2229	0.2874
Prognostics Accuracy (%)	1	1	4.95023e-7	1.1034	0.3113

Figure 22. JMP Regression Output for ALS Operational Availability

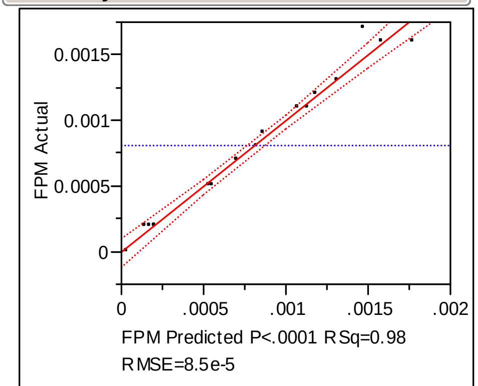
b. Failures Per Mission

Regression is used to fit a linear model to explain the relationship between the predictor variables: module reliability, prognostics accuracy, false positives, depot turn around time, inventory and detection lead time, and the response variable FPM. Figure 23 is the JMP regression report with correlation matrix attached. The parameter estimates table of the report gives the estimated coefficients, their standard errors and the corresponding t-statistics to test the partial effect of each variable. R^2 is 0.98, indicating the regression does a good job in accounting for the variability in FPM. Module reliability and prognostic accuracy are the two predictor variables selected for the linear

model. Prognostic accuracy has the heaviest weight value on the expected value of FPM followed by module reliability and the interaction between prognostics accuracy and module reliability.

Response FPM

Actual by Predicted Plot



Summary of Fit

RSquare	0.981146
RSquare Adj	0.976796
Root Mean Square Error	0.000085
Mean of Response	0.000812
Observations (or Sum Wgts)	17

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Ratio
Model	3	0.00000486	0.0000016	225.5073
Error	13	9.34697e-8	7.19e-9	Prob > F
C. Total	16	0.00000496		<.0001

Parameter Estimates

Term	Estimate	Std Error	t Ratio	Prob>|t
Intercept	0.0167315	0.000646	25.91	<.0001
Module Reliabilty (flight hrs)	-5.982e-7	6.771e-8	-8.83	<.0001
Prognostics Accuracy (%)	-0.016429	0.000678	-24.23	<.0001
(Module Reliabilty (flight hrs)-505.882)*(Prognostics Accuracy (%)-0.95059)	0.00001	0.000002	4.40	0.0007

Effect Tests

Source	Nparm	DF	Sum of Squares	F Ratio	Prob > F
Module Reliabilty (flight hrs)	1	1	5.61225e-7	78.0566	<.0001
Prognostics Accuracy (%)	1	1	0.00000422	587.2160	<.0001
Module Reliabilty (flight hrs)*Prognostics Accuracy (%)	1	1	1.3944e-7	19.3937	0.0007

Corr

	Intercept	R		P(R-505.882)*(P-0.95059)
Intercept	1.0000	-0.0518	-0.9981	0.0557
R	-0.0518	1.0000	-0.0012	0.0283
P	-0.9981	-0.0012	1.0000	-0.0573
(R-505.882)*(P-0.95059)	0.0557	0.0283	-0.0573	1.0000

R = module reliability, P= prognostic accuracy

Figure 23. JMP Regression Report for ALS FPM

The scatter plot matrix, Figure 24, indicates there is no collinearity between module reliability and prognostic accuracy. The plot shows a moderate linear relationship between module reliability and FPM. However, the plot also shows a stronger linear relationship between prognostic accuracy and FPM. This supports the fitted regression model:

$$0.167 - (5.9\text{e-}7 * \text{reliability}) - (0.016 * \text{prognostics}) + (0.0001 * (\text{reliability} - 505.9) * (\text{prognostics} - 0.95)$$

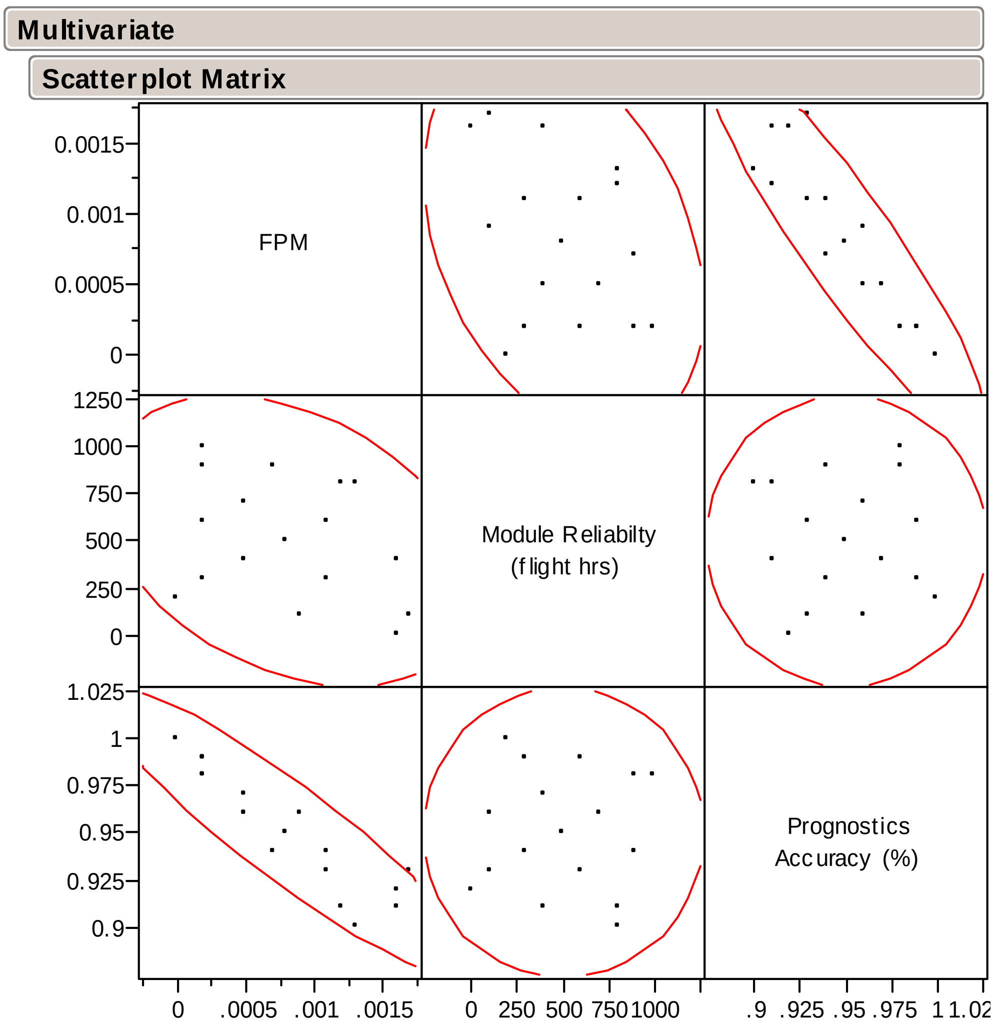


Figure 24. Scatter Plot Matrix ALS FPM

Figure 25, is a contour plot, comparing module reliability and prognostic accuracy in terms of FPM. Note the color pattern tends to be horizontal and slightly tilted, indicating prognostic accuracy is more important. The tilt in the contour plot indicates including an interaction between module reliability and prognostic accuracy helps predicting FPM. The interaction term is included in the regression. This provides further evidence in support of the fitted regression model.

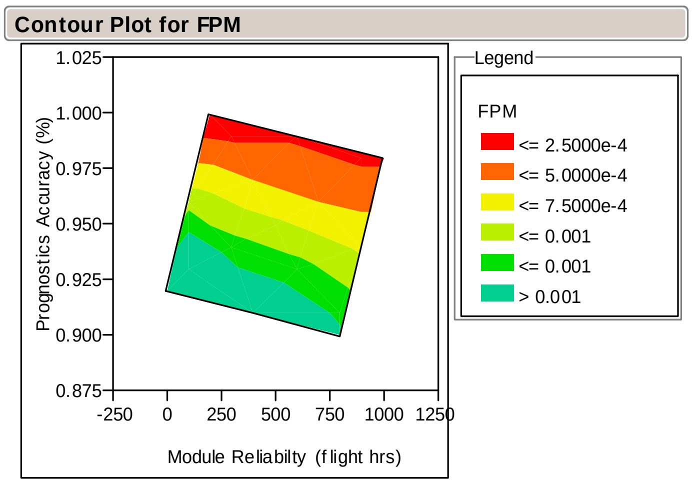


Figure 25. Contour Plot ALS FPM

Figure 26 is a plot of the MMHF linear model of the traditional repair system over the build window range with no improvement in module reliability range. The fitted regression model predicts a decrease in FPM when prognostic accuracy increases or when module reliability increases. Linear programming is used to optimize the FPM regression model with the predictor variable ranges as constraints. Setting both prognostic accuracy module reliability to the highest value in their respective range yield the optimal (smallest) FPM. Prognostic accuracy is set to 1.0 and module reliability is set 1000 hrs. The regression model produces an FPM of 0.00005. The DES model for the ALS produces an FPM of 0.0 with standard error 0.0. The relative difference between the regression model and the simulation models is irrelevant as both essentially equal zero.

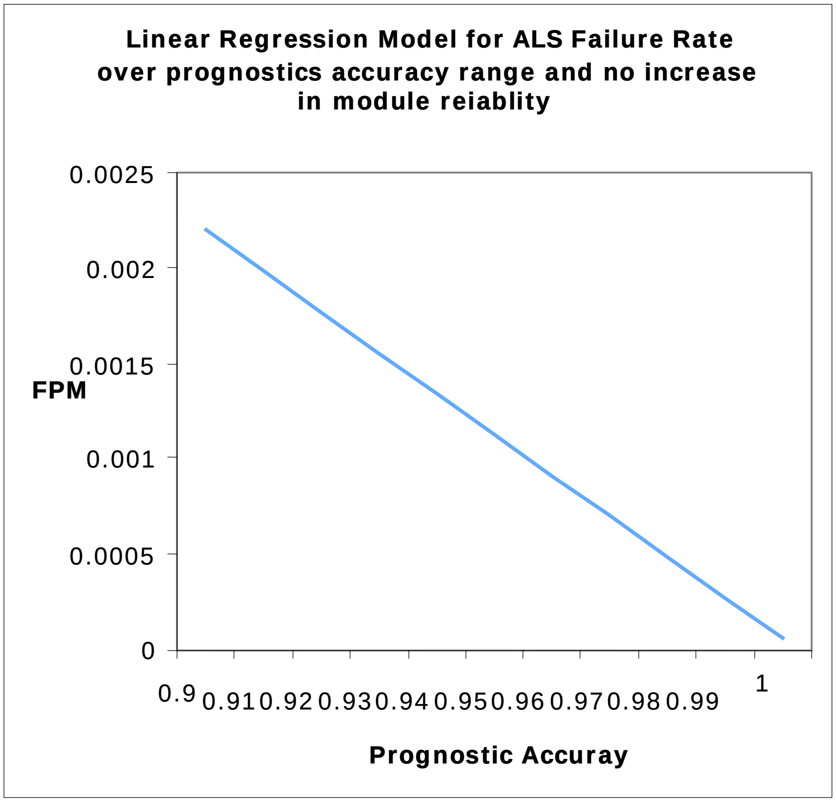


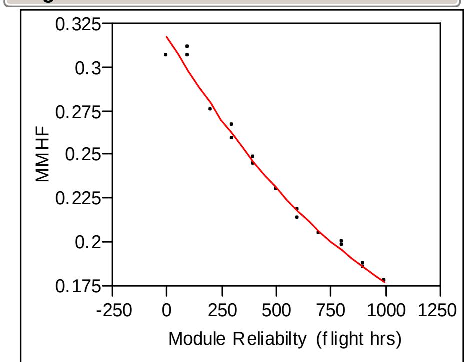
Figure 26. FPM ALS Regression Model for ALS

c. Maintenance Man Hours Per Flight Hour

Regression is used to fit a linear model to explain the relationship between the predictor variables: module reliability, prognostics accuracy, false positives, depot turn around time, inventory and detection lead time, and the response variable MMHF. Figure 27 is the JMP regression report. The parameter estimates table of the report gives the estimated coefficients, their standard errors and the corresponding t-statistics to test the partial effect of each variable. R^2 is 0.984, indicating the regression does a good job in accounting for the variability in MMHF. Module reliability is the only predictor variable chosen for the linear model. False positive is the next significant variable, but not significant enough to be included in the model.

Response MMHF

Regression Plot



Summary of Fit

RSquare	0.984845
RSquare Adj	0.98268
Root Mean Square Error	0.005854
Mean of Response	0.236853
Observations (or Sum Wgts)	17

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Ratio
Model	2	0.03117302	0.015587	454.8869
Error	14	0.00047970	0.000034	Prob > F
C. Total	16	0.03165272		<.0001

Lack Of Fit

Source	DF	Sum of Squares	Mean Square	F Ratio
Lack Of Fit	8	0.00041889	0.000052	5.1659
Pure Error	6	0.00006082	0.000010	Prob > F
Total Error	14	0.00047970		0.0303
				Max RSq
				0.9981

Parameter Estimates

Term	Estimate	Std Error	t Ratio	Prob>|t|
Intercept	0.3013858	0.003221	93.57	<.0001
Module Reliabilty (flight hrs)	-0.000139	0.000005	-29.85	<.0001
(Module Reliabilty (flight hrs)-505.882)*(Module Reliabilty (flight hrs)-505.882)	6.5345e-8	1.75e-8	3.73	0.0022

Effect Tests

Source	Nparm	DF	Sum of Squares	F Ratio	Prob > F
Module Reliabilty (flight hrs)	1	1	0.03052350	890.8178	<.0001
Module Reliabilty (flight hrs)*Module Reliabilty (flight hrs)	1	1	0.00047757	13.9378	0.0022

Figure 27. JMP Regression Report for ALS MMHF

The scatter plot matrix, Figure 28, indicates there is no collinearity between module reliability and false positives. The plot shows a linear relationship between module reliability and MMHF. This supports the findings of the regression model: $0.3 - (0.00014 * \text{reliability}) - (6.5\text{e} - 8 * (\text{reliability} - 505.88)^{\wedge}2)$.

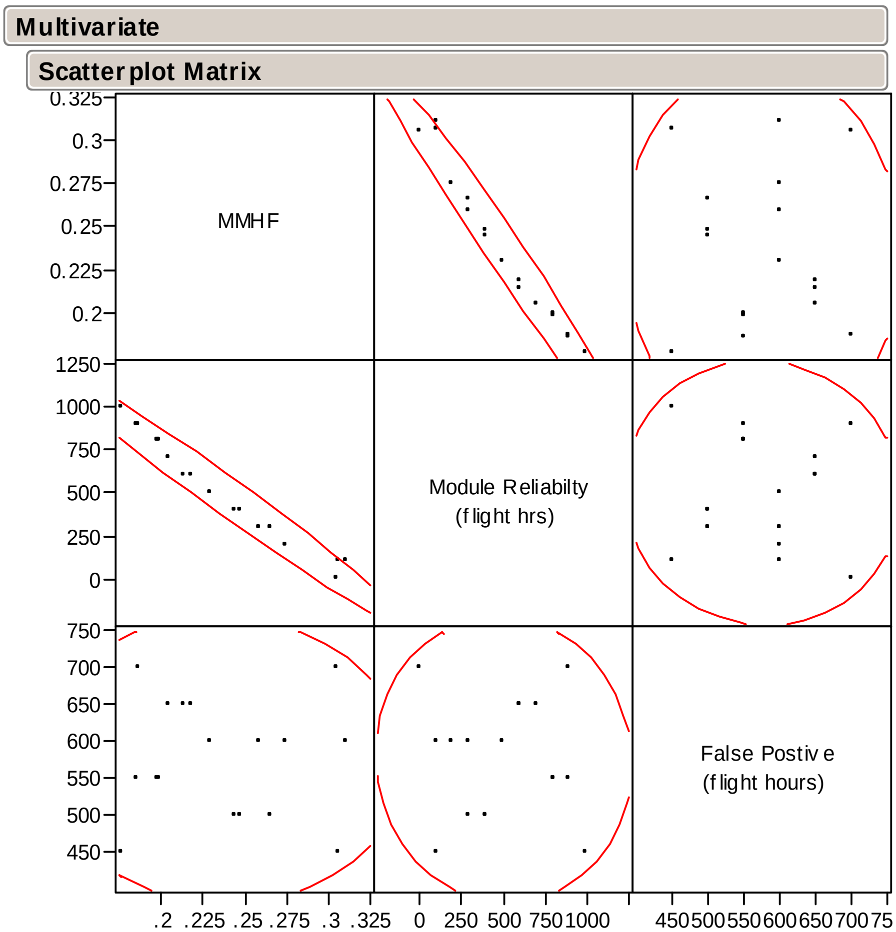


Figure 28. Scatter Plot Matrix ALS MMHF

Figure 29, is a contour plot, comparing module reliability and false positives in terms of MMHF. The vertical coloring pattern suggests failure rate improves with the increase of module reliability and is not affected by false positives. This provides further evidence in support of the fitted regression model.

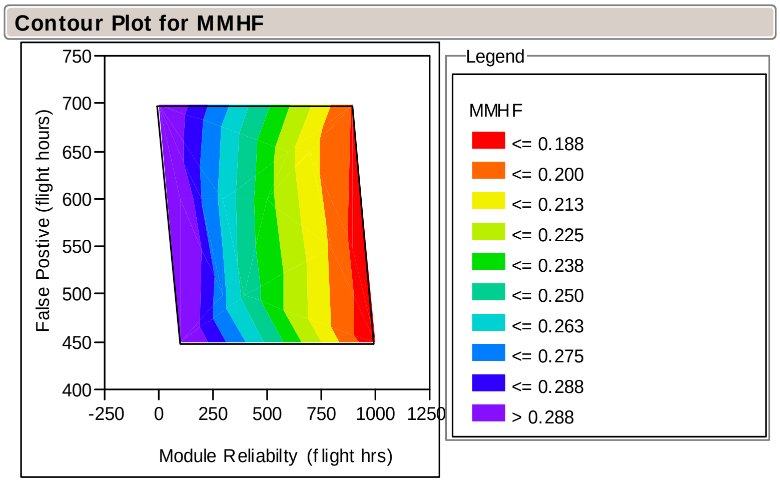


Figure 29. Contour Plot ALS MMHF

Figure 30 is a plot of the MMHF linear model of the ALS system over the module reliability range. The fitted regression model predicts a decrease in MMHF when module reliability increases. Therefore, the largest value of module reliability in the range is used in the regression model to calculate the smallest MMHF. The highest value of the module reliability is 1000 hrs. Module reliability is set to 1000 hrs. The regression model produces an MMHF of 0.17785. The DES model for the ALS produces an MMHF of 0.1590 with standard error 0.0016. The relative difference between the regression model and the simulation model is: 11.8%.

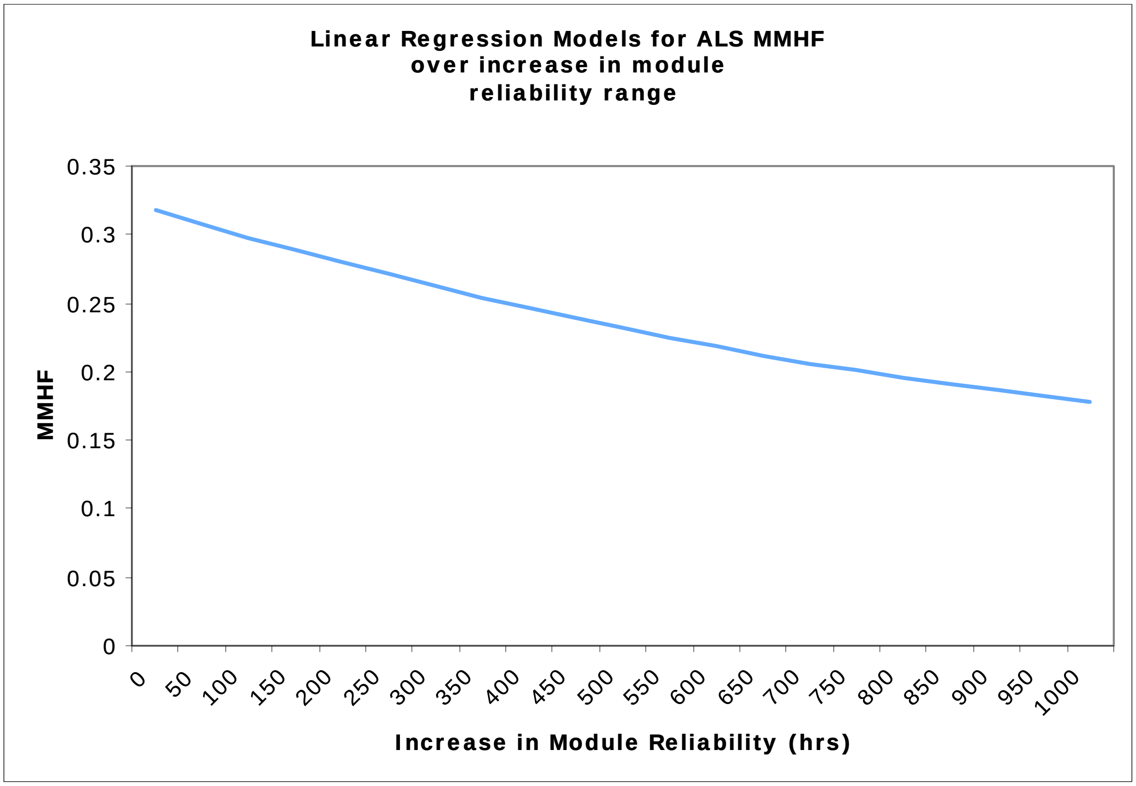


Figure 30. MMHF Regression Model for ALS

E. COMPARING THE TRADITIONAL LOGISTIC SYSTEM TO ALS

For FPM and MMHF linear models can be used to compare the traditional system and the ALS. For operational availability a screening technique is used to compare the traditional system and the ALS.

1. Comparison in Terms of Operational Availability.

The data initially generated consisted of 17 design points. For this data, operational mean for the traditional system is 0.996726 with a standard deviation of 0.000566 and for the ALS is 0.997518 with a standard deviation of 0.0006777. The ALS has the larger mean, but it also has the largest standard deviation. The difference between the two systems is not clear.

Rinott's two-stage screening method is used to select which logistic system is the best. The method is fully explained in (Chen & Kelton, 2000). To use this method it is assumed the data sets are normally distributed. To satisfy the assumption each DES

models was run an additional thirty times. The thirty design points were selected using NOLH. The design points and the corresponding output are listed in Appendix G. In total there are 46 observations for each system. Each data set may be considered normally distributed by applying the general rule of thumb: if a data set is greater than thirty the Central Limit Theorem (CLT) can be used (Devore, 2004, 240). The CLT state large independent random samples (data sets) are approximately normally distributed.

A spreadsheet written by Professor Susan Sanchez, Naval Postgraduate School is used to implement Rinott's two-stage screening method. The ALS is chosen as the best system after the first stage. The second stage is not necessary.

2. Comparison in Terms of FPM

For FPM, the regression indicates module reliability is the most important factor for the traditional system and prognostic accuracy is the most important factor for the ALS. Constraints may preclude investing in both module reliability and prognostic accuracy.

The optimal (smallest) value for the FPM linear model of the traditional repair system is 0.012, when module reliability is 1000 hours. The FPM linear model for the ALS includes prognostic accuracy and module reliability. Since only one variable can change, module reliability is set to a constant zero. This means module reliability is not improved. The optimal (smallest) value is 0.00005 when prognostic accuracy is 1.0. The worst (largest) value is 0.001 when prognostic is 0.9. For the parameter ranges, the prognostic worst case for the ALS yields a lower FPM then the best case for the traditional system. In this case, investing in prognostics is clearly better than investing in module reliability.

In the case when one option does not dominate, graphs like Figure 31 can be used to find the turning point. The turning point is the values for which one option is better or worse than the other. To construct Figure 31, first set the two regression models equal to each other and solve for prognostic accuracy. The result is an equation for prognostic accuracy in terms of module reliability. This is the equilibrium equation. The pair of values of prognostic accuracy and module reliability that satisfy the equation yield the same FPM: in terms of FPM they are equivalent. Thus, investing in one or the other is

the same. Select values above and below the equilibrium line, to determine which option is best. Note the graph of Figure 31 has prognostic accuracy between values of 0.15 and 0.45. This coincides with the conclusion, but the model prognostic accuracy range is 0.9 to 1.0. Therefore, for this case Figure 31 should not be used for further analysis. For the entire parameter ranges the ALS performs better than the traditional repair system. When deciding between investing in module reliability in the traditional repair system or prognostic accuracy it is best to invest in prognostics and switch to ALS.

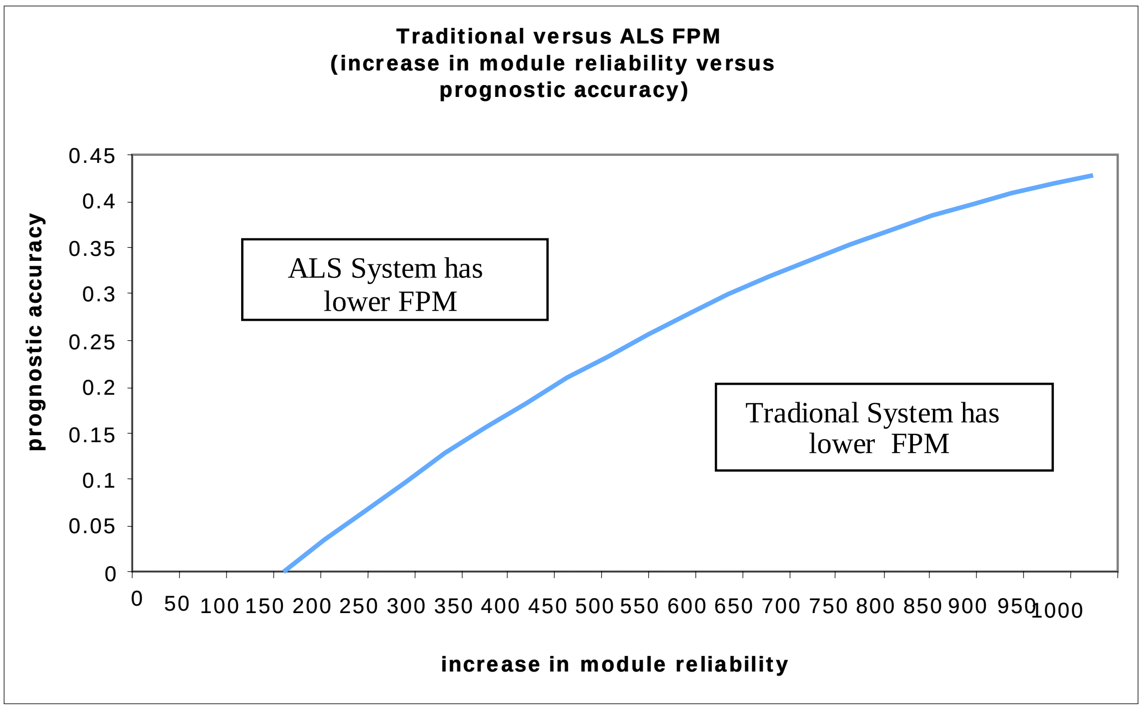


Figure 31. FPM Regression Models, Traditional Repair System Versus ALS

3. Comparison in Terms of MMHF

For MMHF, the regression indicates build window and module reliability are the most important factors for the traditional system and module reliability is the most important factor for the ALS. Two questions are answered: (1) can increasing only build windows for the traditional logistic yield similar of better results then the ALS, (2) with build windows set at the optimal value (500 hrs), is it better to invest in module reliability in the traditional logistics system or the ALS.

First a comparison is made between the linear model of the traditional logistic system over the build window range with no improvement in module reliability range and the ALS model over the module reliability range. Figure 32 is a plot of the equilibrium equation. When no improvement in the ALS module reliability is made the two systems are equivalent when build windows is increased to over 1000 hours. The build window range is 50 to 500 hours. Therefore Figure 32 should not be used for further analysis. The regression models show that within the parameter ranges of the simulation increasing only build windows in the traditional system will yield a higher (worse) MMHF than the ALS.

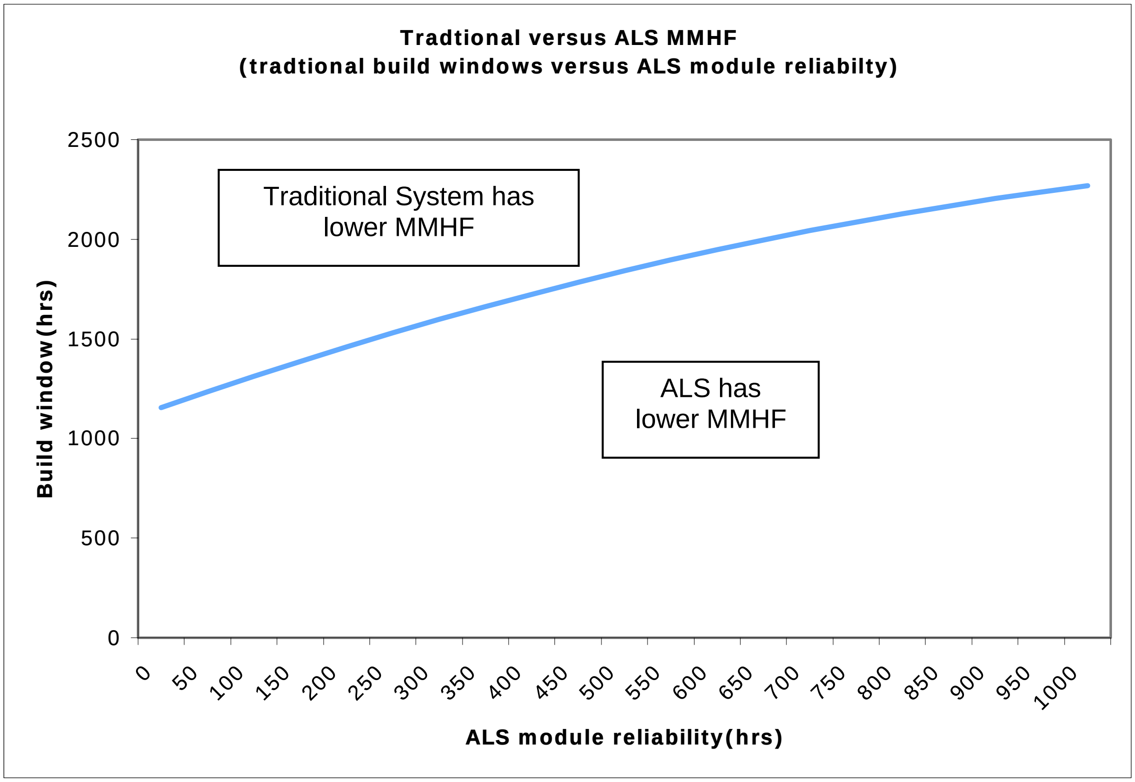


Figure 32. MMHF Regression Models, Traditional Repair System Versus ALS

Next, a comparison is made between the linear model of the traditional logistic system over the module reliability range and build window range set to 500 hours and the ALS model over the module reliability range. Figure 33 is a plot of the equilibrium

equation. When no improvement in the ALS module reliability is made the two systems are equivalent when module reliability is increased by over 500 hours for the traditional system. Eventually as displayed in Figure 33 for the systems to be equivalent module reliability for the traditional system is increased by over 100 hours, which exceed the module reliability range. The regression models show that the deciding between investing in module reliability in the traditional logistics system or in the ALS, it is best to invest in the ALS.

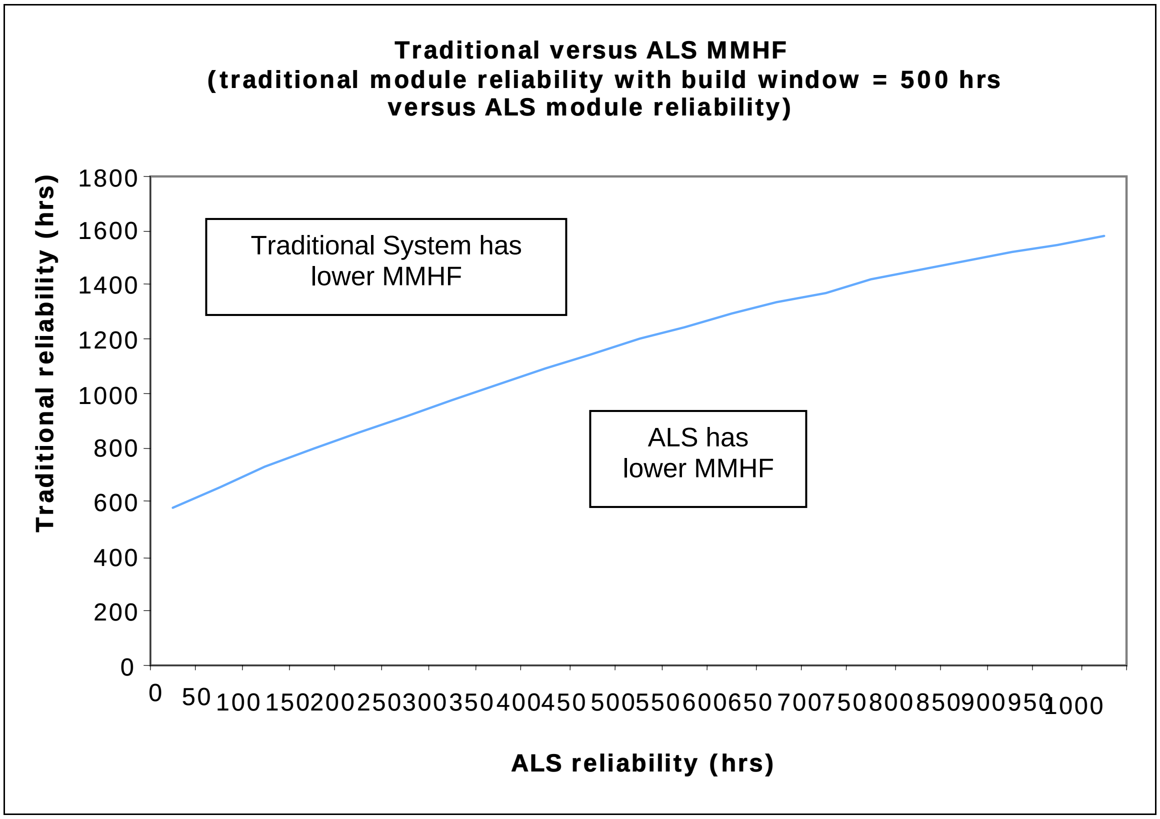


Figure 33. MMHF Regression Models, Traditional Repair System Versus ALS

F. CONCLUSIONS

This chapter outlined the results of the thesis. Design points to drive the simulations were carefully selected to extract as much information as possible from a minimum number of runs. For both systems, regression led to good predictive models for FPM and MMHF, but not operational availability. Additional runs were made to

implement Rinott's screening method to compare the operational availability of both systems. For each of the MOEs, the ALS is the better system. The ALS dominates in terms of FPM and MMHF. However, large gains in operational availability were not realized.

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VI. CONCLUSIONS AND RECOMMENDATIONS

A. CONCLUSIONS

The objective of the thesis was to compare the traditional logistics system to the ALS and analyze the hypothetical benefits of the ALS. Key components necessary to model the system were identified. DES models were developed using Java and Simkit. The DES models and the regression models can be used as decision making tools. The regression models, only apply within the predictor variable ranges.

Conclusions for the traditional repair system:

1. I-level inventory equivalent to that from table 6 with a guaranteed depot turn around time of 40 days is all that is required for operational availability. At these specific values increasing the I-level inventory or decreasing the depot turn around time has a minimal effect on operational availability. At these specific values, the main driver for operational availability is build window.
2. Module reliability is most important in terms of FPM. Shrinking build windows at the I-level does not improve FPM. Shrinking build windows leads to some parts being replaced early and more often at the I-level. Replacing parts more often does not decrease FPM. The parts are on a replacement schedule at the O-level. With the replacement (high time) schedule in place, replacing parts earlier at the I-level does not improve FPM.
3. Module reliability and build windows are the two significant factors for predicting MMHF. They are equally weighted.

Conclusions for the ALS:

1. I-level inventory equivalent to that from table 6 with a guaranteed depot turn around time of 40 days is all that is required for operational availability. At these specific values increasing the I-level inventory or decreasing the depot turn around time has a minimal effect on operational availability. At these specific values, the main driver for operational availability is prognostic accuracy followed by module reliability.
2. Module reliability and prognostic accuracy are the significant factors in the FPM model. Module reliability is weighted more heavily then prognostic accuracy.
3. Module reliability is the only significant factor in predicting MMHF.

For FPM, the regression models show that when deciding between investing in module reliability in the traditional repair system or prognostic accuracy it is best to invest in prognostics and switch to ALS. In fact, within the parameter ranges of the simulation, the worst FPM rate for ALS was better than the best FPM rate for the traditional repair system.

The analysis shows that when operational availability is the criteria used to distinguish between the two systems, the ALS is selected as the best. A performance based logistic contract which guarantees delivery of components within a certain time frame makes the two logistic systems more equivalent.

For MMHF, the regression models show that when deciding between investing in module reliability in the traditional repair system or to invest in module reliability in the ALS, it is best to switch to the ALS. The ALS with no improvements is equivalent to increasing both build window and module reliability to the maximum value for the traditional system. The ALS potential far exceeds that of the traditional logistic system.

B. RECOMMENDATIONS FOR FURTHER STUDY

Potential follow-on-studies include researching the effects of:

- different module replacement schedules (high time).
- different flight schedules.
- longer depot turn around times, to gain an understanding of when depot turn around time impacts operational availability.
- different ranges for the predictor variables.

Further enhancements to the DES models may be applied:

- Include the depot level in detail.
- Model actual individual maintainers and equipment.
- As the JSF ALS is better defined, adjust the DES.

C. CONCLUSION AND RECOMMENDATION ABOUT THE ALS

For each MOE, the ALS out performed the traditional logistics system. The ALS with prognostic accuracy of at least 0.9 and an exponential mean time between false positives of no more than 700 hours dominates the traditional system in terms of FPM

and MMHF. Within the scope of the thesis, the traditional system was never found to be the better option. The ALS is superior to the traditional repair system.

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APPENDIX A. DATA VALUES

The following data were obtained from Lieutenant Commander Schoch's thesis (Schoch, 2003):

I-level site chosen: Pax River
Number of O-levels: 1
Number of aircraft: 25

Part	High Times (hrs)	I	R	O-level Trouble shooting time	I-level Inspection Time	T
Fan	1100,2000,2200, 4000,5350,7175, 7342,7575,10700	7	2.4	N/A	N/A	N/A
Compressor	2000,2967,3075, 3800,4000,4150, 4717,8117	3	2.71	N/A	N/A	N/A
Combustor	2000	4	1.43	N/A	N/A	N/A
HPT	1203,1542,2200, 2417,2483	2	2.27	N/A	N/A	N/A
LPT	2000,4000,4242, 16625,19025	1	1.31	N/A	N/A	N/A
Afterburner	2000	2	1.6	N/A	N/A	N/A
Engine	N/A	8	3.3	3.34	4.5	0
I = Inventory levels R = Install / Removal times (hrs) T = O-level to I-level transfer time (hrs)						

Table 6. Data Values

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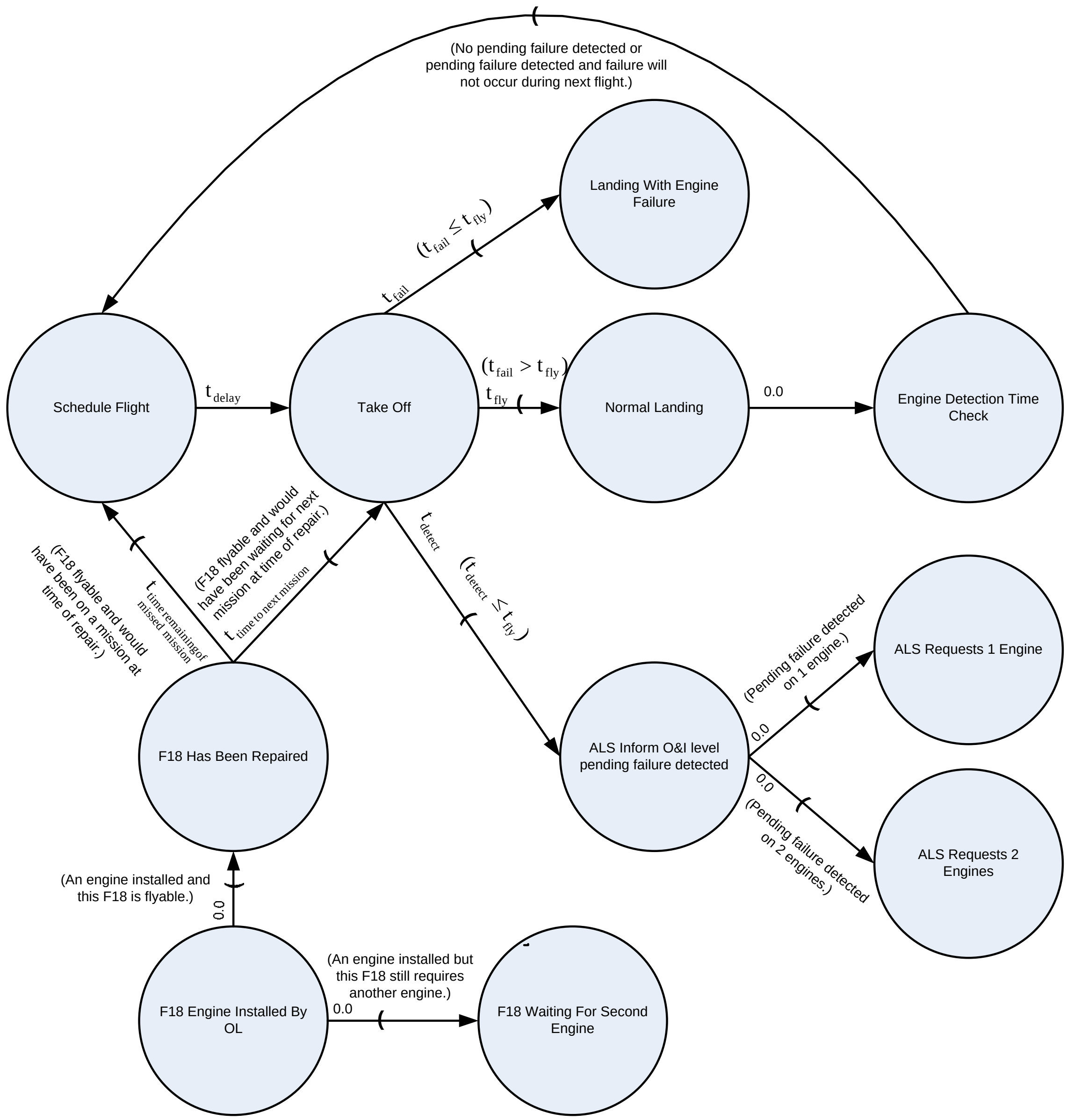
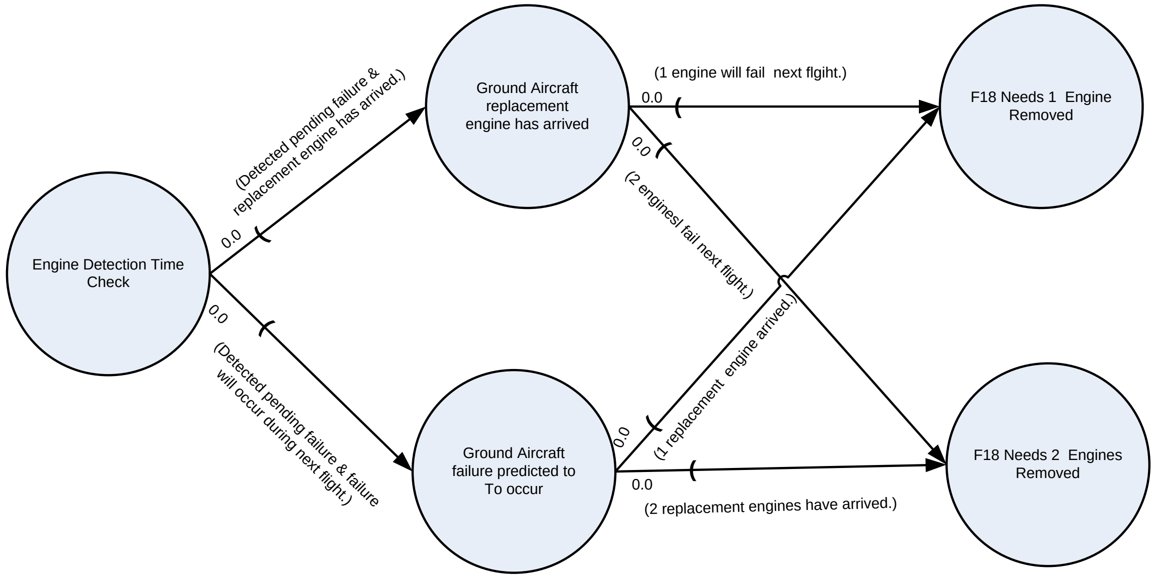
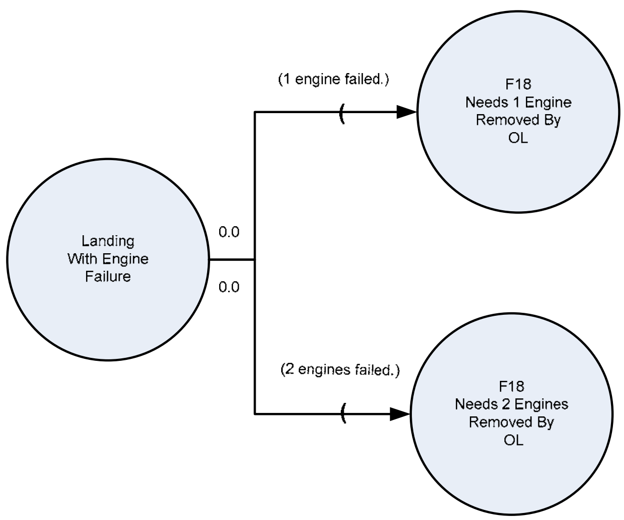
APPENDIX B. ALS F18 HORNET EVENT GRAPH



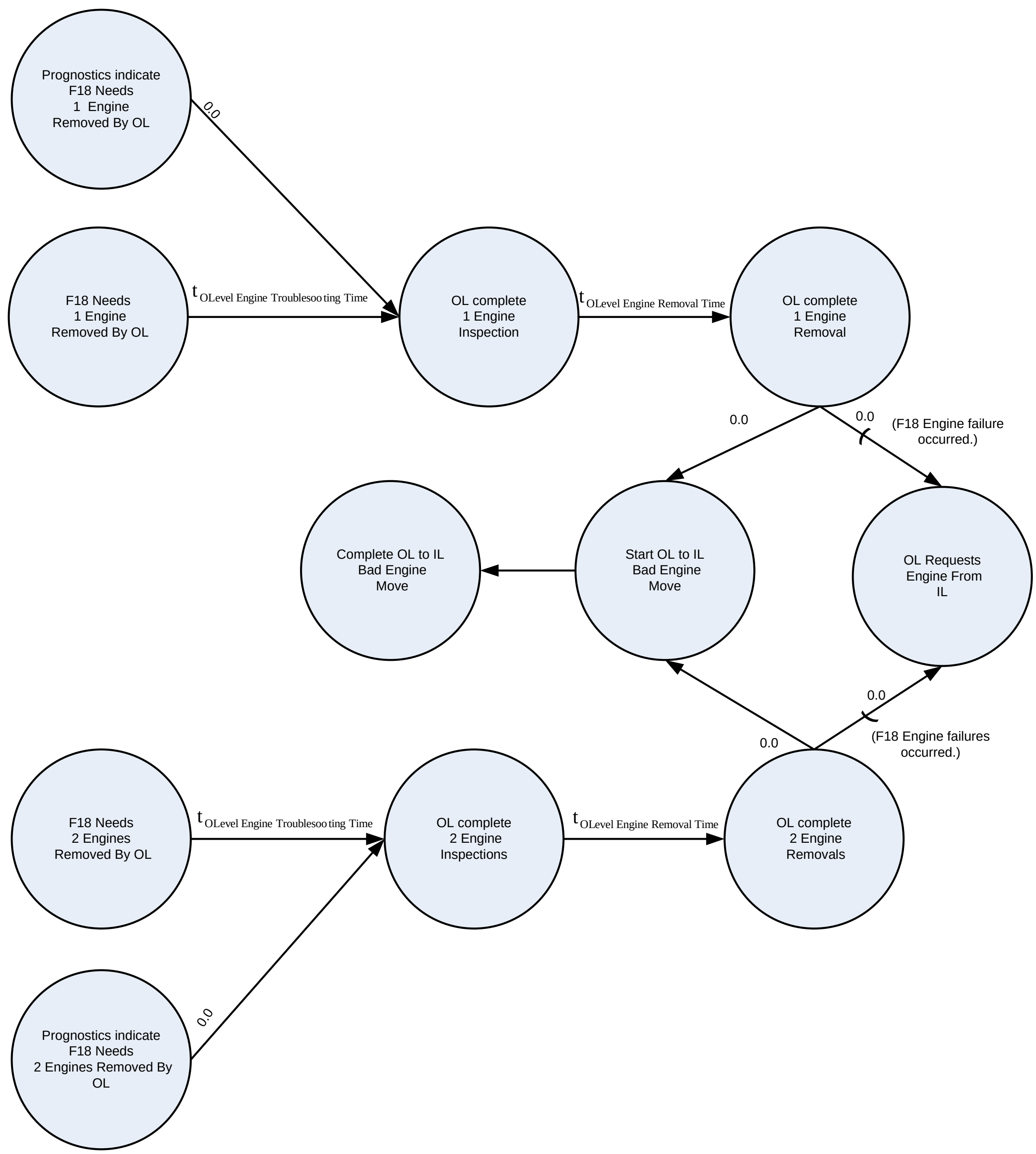


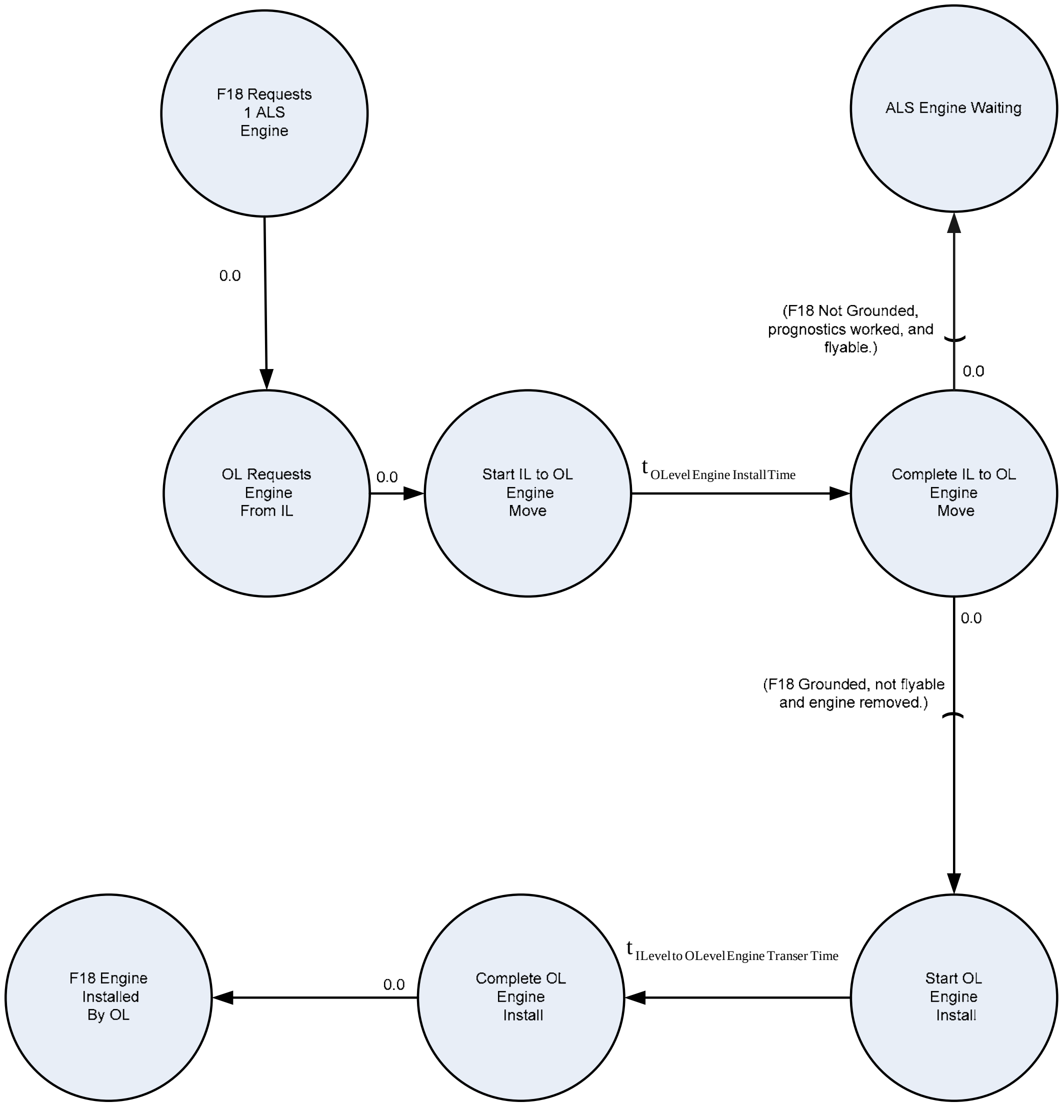
Engine Detection Time Check
(Detected pending failure & replacement engine has arrived.)
0.0
Ground Aircraft replacement engine has arrived
(1 engine will fail next flgiht.)
0.0
F18 Needs 1 Engine Removed
0.0
(2 enginesl fail next flight.)
0.0
(Detected pending failure & failure will occur during next flight.)
Ground Aircraft failure predicted to To occur
0.0
(1 replacement engine arrived.)
0.0
(2 replacement engines have arrived.)
F18 Needs 2 Engines Removed



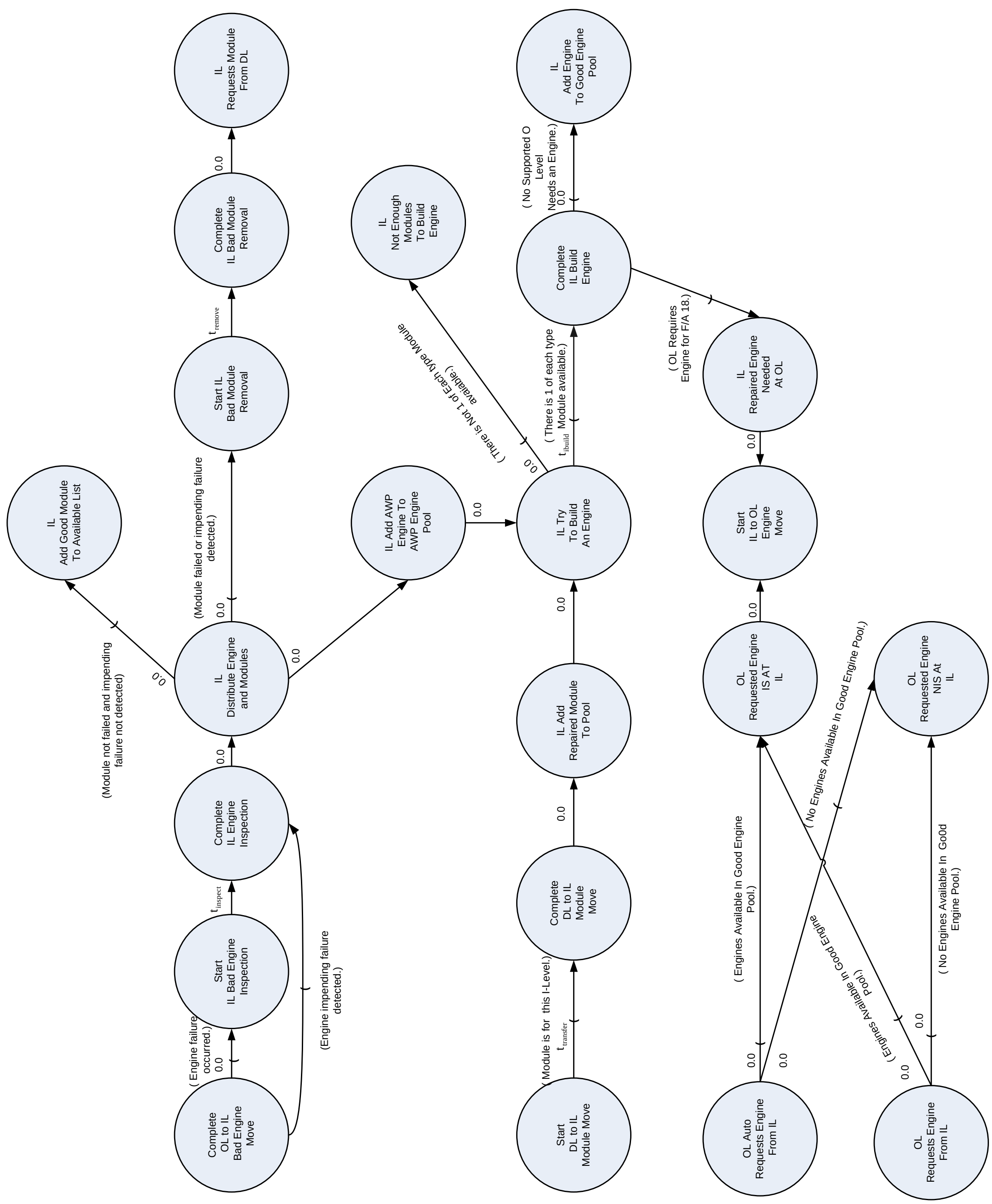
Landing With Engine Failure
0.0
0.0
(1 engine failed.)
F18 Needs 1 Engine Removed By OL
(2 engines failed.)
F18 Needs 2 Engines Removed By OL

APPENDIX C. ALS O-LEVEL EVENT GRAPH




F18 Requests 1 ALS Engine
0.0
ALS Engine Waiting
(F18 Not Grounded, prognostics worked, and flyable.)
0.0
OL Requests Engine From IL
0.0
Start IL to OL Engine Move
t OLevel Engine Install Time
Complete IL to OL Engine Move
0.0
(F18 Grounded, not flyable and engine removed.)
F18 Engine Installed By OL
0.0
Complete OL Engine Install
t ILevel to OLevel Engine Transer Time
Start OL Engine Install

APPENDIX D. ALS I LEVEL EVENT GRAPH



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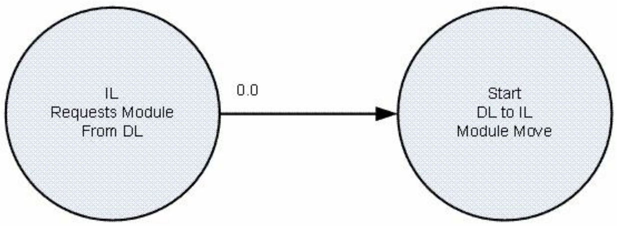
APPENDIX E. ALS D-LEVEL EVENT GRAPH



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APPENDIX F. AGE REPLACEMENT POLICY

The following is the long run average failure rate model for the age replacement policy by Professor Patricia Jacobs, Naval Postgraduate School:

An age replacement policy class for an item upon its failure or upon it reaching age T whichever occurs first:

Replacement items are as good as new. Let L_i be the i^{th} lifetime. Assume $L_{1,} L_2, \ldots$ are independent identically distributed having a distribution function F with density f. Let $Y_1, Y_2 \ldots$ denote the times between successive failures. Let $N_f(t)$ be the number of failures to occur during $(0,t]$. $\{N_f(t); t \geq 0\}$ is a possibly delayed renewal counting process with inter-renewal times $\{Y_i\}$, $\lim_{t\to\infty} \frac{N_f(t)}{t} = \frac{1}{E[y_2]}$ with probability 1.

To find $E[Y_2]$:

The random variable Y_2 is comprised of a random number of time periods of length T (corresponds to replacements not associated with failures) plus a last time period for which the distribution is that of a failure conditioned on failure before age T.

$$
\begin{aligned}
&Y_2 = NT + U \\
&P\{N \geq k\} = [1 - F(T)]^k \;\; for\ k = 1,2\ldots \\
&P\{U \leq u\} = P\{L \leq u \mid L \leq T\} = \frac{P\{L \leq u, L \leq T\}}{P\{L \leq T\}} \\
&\qquad = 0 \qquad if\ u \leq 0 \\
&\qquad = \frac{F(u)}{F(T)} \quad if\ 0 \leq u \leq T \\
&\qquad = 1 \qquad if\ u > T
\end{aligned}
$$

Result: Let N be a nonnegative random variable.

$$E[N] = \sum_{n=0}^{\infty} np\{N = n\} = \sum_{n=1}^{\infty} P\{N \geq n\} = \sum_{n=0}^{\infty} P\{N > n\}$$

Using the result in this example

$$E[N] = \sum_{n=1}^{\infty} P\{N \geq n\} = \sum_{n=1}^{\infty} [1 - F(T)]^n = \frac{1 - F_L(T)}{F_L(T)}$$

$$E[U] = \int_0^T u \frac{f(u)}{F(T)} du$$

$$E[Y_2] = E[NT + U] = E[N]T + E[U] = \frac{[1 - F(T)]T}{F(T)} + \int_0^T u \frac{f(u)}{F(T)} du$$

(Jacobs, 2005, 12-13)

<u>STATEMENT</u>: If the lifetime distribution is exponential then the log run average number of failures under age replacement policy is the same as the long run average number of failures when the item is replaced upon failure alone.

<u>Proof:</u>

$$E[Y_2] = E[NT + U] = E\lambda[N]T + E[U] = \frac{[1 - F(T)]T}{F(T)} + \int_0^T u \frac{f(u)}{F(T)} du$$

$$let\ a = \frac{[1 - F(T)]T}{F(T)} = \frac{Te^{-\lambda T}}{(1 - e^{-\lambda T})}$$

$$let\ b = \int_0^T u \frac{f(u)}{F(T)} du = \frac{1}{(1 - e^{-\lambda T})} \int_0^T ue^{-\lambda u} du$$

$$= \frac{1}{(1 - e^{-\lambda T})} \frac{1}{\lambda} \left[-\lambda e^{-\lambda u} - e^{-\lambda u}\right]_0^T$$

$$= \frac{1}{(1 - e^{-\lambda T})} \frac{1}{\lambda} \left[1 - e^{-\lambda T} + 1\right]$$

$$a + b = \frac{Te^{-\lambda T} - Te^{-\lambda T} + [1 - e^{-\lambda T}]/\lambda}{(1 - e^{-\lambda T})} = \frac{1}{\lambda}$$

$$\Rightarrow E[Y_2] = \frac{1}{\lambda}$$

but $\frac{1}{\lambda}$ = expected time of failure due to age if lifetime exponentially distributed.

Therefore, the statement is correct.

APPENDIX G. ADDITIONAL SIMULATION RUNS

Traditional Model

Input				Output
Reliability	**Depot (hrs)**	**Inventory**	**Build window**	**Availability**
(hrs)	**(days)**	**(modules)**	**(hrs)**	
10	30	8	200	0.995
60	40	7	150	0.9948
100	20	8	300	0.9952
10	30	1	350	0.9952
80	10	7	400	0.9954
100	20	4	500	0.9955
70	30	2	400	0.9953
100	35	10	350	0.9953
50	10	2	400	0.9953
90	15	9	150	0.9948
80	30	11	100	0.9947
70	40	6	450	0.9955
30	35	4	500	0.9955
20	35	8	450	0.9955
100	40	4	250	0.9951
70	25	5	250	0.9951
20	35	3	150	0.9948
30	20	11	100	0.9947
40	20	7	50	0.9945
80	25	11	500	0.9956
40	40	5	300	0.9952
60	30	10	300	0.9952
50	25	6	450	0.9954
40	40	11	350	0.9953
90	15	2	300	0.9952
30	15	9	500	0.9955
90	25	3	100	0.9947
10	20	6	400	0.9954
50	10	10	250	0.9951
Depot = depot turn around time				

Table 7. ALS additional runs

ALS						
Input						Output
Reliability	Depot (hrs)	Inventory	Prognostics	False Postives	Lead Time	Availability
(hrs)	(days)	(module)	(fraction)	(hrs)	(hrs)	
0	10	9	0.94	600	15	0.9995
100	30	8	0.97	650	30	0.9966
600	40	7	0.98	700	25	0.9976
1000	20	8	0.93	650	40	0.998
100	30	1	0.94	650	20	0.9966
800	10	7	0.99	550	35	0.9978
1000	20	4	0.99	600	25	0.998
700	30	2	0.95	500	40	0.9977
1000	35	10	0.96	500	40	0.998
500	10	2	0.91	650	40	0.9974
900	15	9	0.99	550	20	0.9979
800	30	11	0.93	650	20	0.9978
700	40	6	0.91	700	30	0.9977
300	35	4	0.92	600	35	0.9971
200	35	8	1	600	35	0.9968
1000	40	4	0.92	650	25	0.998
700	25	5	1	550	35	0.9977
200	35	3	0.96	600	40	0.9968
300	20	11	0.98	650	30	0.9971
400	20	7	0.97	500	25	0.9972
800	25	11	0.95	450	20	0.9978
400	40	5	1	650	20	0.9973
600	30	10	1	550	35	0.9976
500	25	6	0.99	650	25	0.9974
400	40	11	0.91	600	20	0.9972
900	15	2	0.95	650	30	0.9979
300	15	9	0.93	500	30	0.9971
900	25	3	0.92	550	30	0.9978
100	20	6	0.98	500	35	0.9966
500	10	10	0.94	500	20	0.9974
F= False positive rate						
Depot = Depot turn around time						
Lead = Detection Lead Time						

Table 8. ALS additional runs

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